MODELING TASTE CHANGE IN MEAT DEMAND: AN APPLICATION OF LATENT STRUCTURAL EQUATION MODELS

BY

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To my parents

Gao Jisheng and Nian Guizhen

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It has been a long process to complete this dissertation. The experience and knowledge I gained through this study are marvelous and can't be over estimated.

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Taste or preference comprises an unobservable latent variable in utility and demand functions. This latent variable can be estimated by using both its indicator and causal variables in a structural equations model. It is widely presumed that taste changes in the last three decades have significantly affected U.S. consumer demand for meat products. This dissertation uses both static and dynamic latent variable models to estimate the latent taste variable in a U.S. meat demand system. The static latent variable model is estimated by using factor analysis and causal path analysis; the dynamic latent variable model uses a state space model estimated by Kalman filtering and smoothing. Empirical results show that taste changes have been a significant factor explaining both declining beef and increasing poultry per capita consumption. The taste change is attributed to consumer health concerns over fat and

cholesterol intake and demand for convenience food. It is estimated that consumer taste change has decreased per capita consumption of beef by twenty-four percent over the last three decades and increased that of poultry by sixty-five percent and the trend continues. Taste elasticity is increasing, showing that consumer are more responsive to taste changes. This is because health information is more readily available, consumers are more health conscious, and demand for convenience increases as more married women are working.

CHAPTER 1
INTRODUCTION

For the past quarter of century there have been significant changes in U.S. food consumption patterns. The per capita consumption of some foods has increased while the consumption of others has declined. Consumers are purchasing smaller quantities of dairy products, grains, and cereals and are consuming more poultry and fish, fat and oil, fruits and vegetables, potatoes, and sweets. The total quantity of meat, poultry, and fish consumptions is higher now than in the early 1960s and it has changed little since the early 1970s.

When we examine the subgroups that make up meat and dairy products, it is clear that consumers have been substituting one product for another. Within dairy products, cheese consumption has increased, while fluid milk and animal fat consumption has decreased. For fluid milk, low fat and skim milk consumption is increasing while whole milk consumption is declining. Now consumers buy more low fat and skim milk than whole milk. Per capita consumption of poultry and vegetable fats has more than doubled, while pork and beef consumption has been stable or increased little.

Meat production is an important sector in agriculture. In the 1987, more than 27 percent of gross farm income came from livestock production (including beef, pork and poultry) of which, beef and pork production accounts for 60 to 70 percent. While total supply of red meats has been relatively stable, its share of the total meat supply has been declining over the past three decades. Poultry production, on the contrary, has been steadily increasing over the same period; it now accounts for about 25 percent of total meat supply. The three products beef, pork, and poultry make up more than 85 percent of the total U.S. meat supply, with fish, veal, lamb, and other minor red meats making up the other 15 percent. The consumption of meat products takes a great proportion of consumer household food expenditure. In 1988, for every dollar which the consumer spent on food at home, approximately 30 cents were allocated to meats, of which more than half was spent on red meat and another 20 percent was spent on poultry (Agricultural Statistics, USDA, 1988).

Red meat and poultry have been and continue to be a major component of the U.S. food system. Thus, it is not surprising that changes in the market conditions for this food group are of great concern and interest to many people. For producers, market changes may mean the need to adjust their market strategies and improve their commodity to satisfy customers; for consumers, changes in market

conditions may mean changing retail prices and availability of commodities. When we examine per capita meat consumption over the last twenty years (Figure 1), it is clear that per capita consumption of meat products has changed substantially.

It is the task of this research to look at the reasons for this change. First, we need to keep in mind that purchasing decisions of consumers are the end result of complex interactions among economic, sociological and psychological factors. These factors express themselves in demand theory as price and income effects, demographic factors, taste, etc. In addition, the values of economic variables will be affected by the interaction of factors such as production level, government policies, and macroeconomic conditions. When we try to dissect these factors using econometric models, it is essential that we do not exclude any of these factors from the analysis which would render conclusions biased (or inconsistent). Different studies on meat demand have addressed the impact of different factors on consumer demand in numerous ways, and empirical measures of demand parameters differ from study to study. Model specification, variable specification, time period of analysis, length of the observation period, and assumptions about functional form all affect demand parameter estimates. While researchers should consider as many factors in demand models as possible

to minimize this biasedness, every study has to focus its attention on one or few factors in empirical analysis. In this study, the effect of a change of taste is the focus.

The change of taste for meat can be affected by different things. One factor is the consumer health concern over blood cholesterol level and saturated fat intake; another is convenience, which in itself is influenced by grading and packing; the third factor is advertising. The hypothesis that consumers are concerned about their health and about the role of different foods in human health has been documented in some public attitude surveys of different population groups and news reports (Myers,1989). But the link between attitudes, as expressed in survey responses, and taste change has not been subjected to rigorous empirical testing. This research will try to shed some light on this aspect.

Problem Statement

Since the early '80s, there has been continuous discussion among agriculture economists concerning possible structural or taste changes in meat demands, especially beef and chicken. The debate stimulated even unusual media coverage (for example, Business Week, 26 August, 28 October, 1985) reflecting public concerns on this issue. These articles argue that consumer blood cholesterol and other nutritional and health concerns may have generated a

departure in meat demand from old long-term trends, and that people tend to buy more white meat and less red meat. Studies finished so far, however, give us mixed results. Moreover, suspicion has arisen among some researchers whether the methodologies employed by previous studies were able to identify structural change (Chalfant & Alston, 1988). More recently, an article by Purcell (1989) blamed agricultural economists for failing to come to a consensus on this issue and alarmed industry leaders with regards to the degree of changing beef demand. The author argues that because the beef industry did not respond to the changes in a timely fashion, it has suffered dearly from shrinking herds, low cattle prices, forced disinvestment and business losses; consumers also suffered from higher retail prices and lack of variety.

The consumption patterns of meat products have changed significantly in the last two decades. Figure 1 shows the annual per capita consumption patterns (pounds of retail equivalent) for beef, pork and poultry. Poultry (including chicken and turkey) consumption has been steadily increasing; total consumption has increased 70 percent from 1965 to 1988, and chicken itself increased by 72 percent. The per capita consumption of beef reached its peak in 1976, and then declined sharply in the second half of the decade. Compared to beef and pork, the relative price of poultry has been declining (Figure 2). Relative prices of beef

increased during the period of late 1970s and slightly decreased in the 1980s. Pork price and consumption have been relatively stable.

The limited data on relative prices and per capita consumption, as well as budget shares of meat products, show that total consumption of beef and poultry has changed and deviated from old trends. At the first glance, it may be hypothesized that observed meat consumption changes are caused by movements in, or fluctuations of, meat prices, consumer incomes, and the prices of substitute goods, all of which interact with stable meat demand functions. There is some credence for this assumption because increasing consumption of poultry is consistent with decreasing relative poultry prices and increasing beef prices (substitutes); and decreasing beef consumption is consistent with higher beef price and declining substitute prices. In addition to this assumption, the change in the consumption pattern may also have been caused by a change in the structure of meat demand resulting from changes in demographic variables, demand for convenience foods, and, above all, from an evolution in consumer preferences driven by a growing awareness of the health hazard of large intake of cholesterol and other saturated fats. The identification of causes of shifts in consumption is extremely important for industry and agricultural economists. The importance of this issue prods researchers to look beyond the simple

assumption of stable demand functions. Indeed, if the beef consumption decline is due to price-income changes, the beef industry must improve its production efficiency if the industry is to keep from shrinking further. If, however, there has been a structural shift in the demand for beef, the industry needs to pursue the question of why preference relations have changed and undertake such measures as advertising, consumer educational programs, grading and packing changes,etc., which could shift preferences back toward their original position.

Of course, consumption is determined by the equilibrium of demand and supply. Consumption changes can come from a shift in supply, a shift in demand, or a combination of the two. A difficult task of structural change studies is to identify the sources of the changes. Supply and demand conditions should be looked at carefully and some clue on forces of change be identified before one starts estimating a sophisticated demand (supply) model, or some form of supply (demand) instrument should be included into demand (supply) models if data permits to avoid simultaneous equation bias. Increases in per capita consumption at higher inflation-adjusted prices are a sure sign of increasing demand. However, beef consumption shows us a different example. From 1979 to 1986, to obtain the same per capita supply of beef sold, the deflated price of choice beef at retail had to drop over 32 percent. Meanwhile,

production costs increased and farm disinvestment continued; this evidence points to a scenario of decreasing demand. Other studies have concluded that the supply shocks are relatively small and have uniform impacts on all meat products (Purcell 1989, Thurman 1987).

Beside the practical importance of advising and helping the meat industry to adjust to changing demand, the identification of the structure of taste change has theoretical importance, which, if not fully acknowledged, can make the estimated demand system neither applicable to the period before nor after the structural change. Most of the studies on structural changes have used a demand system, and have estimated and tested the stability of the parameters. This approach is valid only if the demand system is complete, i.e. the prices and quantities of substitute and complementary goods are included, otherwise the shift of demand function could be caused by a change in an excluded price interacting with a stable demand structure. Furthermore, even with a complete demand system, which satisfies an acceptable definition of flexibility and imposes the restrictions of utility maximization, evidence of structural change may reflect model misspecification of some kind because important features of the data generating process are not known (e.g. the specification of utility function) or are overly simplified. However, the problem can be solved if we make sure that the analysis is carried

out within a functional form which is at least a second order Taylor series approximation of the true demand system. Another alternative is Fourier transform (Wohlgenant, 1984). All the theoretical restrictions of a proper demand system should also be tested and imposed. It is recommended that a taste variable be specifically stated in the model. This added dimension of a demand system will correct the biasedness of other parameter estimates, in terms of omitted variables, and improve the performance of the model in terms of satisfying symmetry and homogeneity conditions (Pope et al. 1980, Stapelton 1984). Relaxing the assumption of constant taste and incorporating it into a indirect objective function (cost or utility function) will make the theoretical structural assumptions tractable.

The proposed research uses the Almost Ideal Demand System (AIDS) developed by Deaton and Muellbauer (1980) and the Rotterdam Model as frameworks for demand analysis. Both of these models have been widely used in demand studies and can be used to provide statistical tests of demand properties. Latent taste variables are specifically included into the objection function, utility and cost functions, to minimize the problem of misspecification.

Organization

This research will specify a structural equation model of meat consumption with provision for static and/or dynamic

latent variables to capture taste changes. Tastes or preferences comprise an unobservable latent variable in the utility and demand functions. The model used in this study will trace the path of taste variable changes and specifically quantify taste changes. The organization of this dissertation is as follows: chapter 2 will review previous studies of structural change in meat demand; chapter 3 reviews and specifies static and dynamic latent variable models used in this study; chapter 4 shows the detailed model specification and set-up of the latent variable model and the selection of cause and indicator variables; chapter 5 shows results of model estimation and chapter 6 gives summary and conclusions.

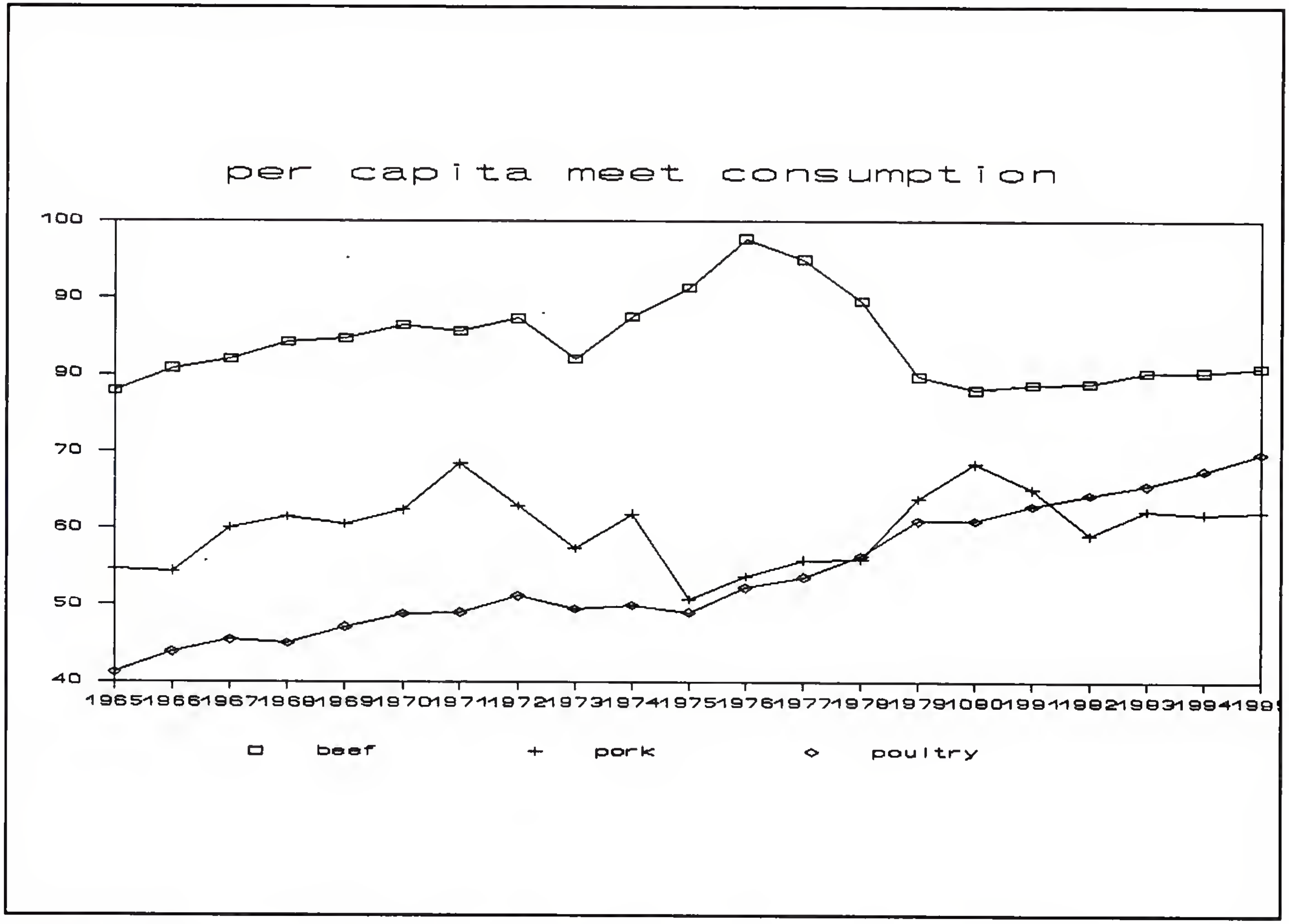

Figure 1. Per Capita Consumption of Three Meats, 1965-1985.

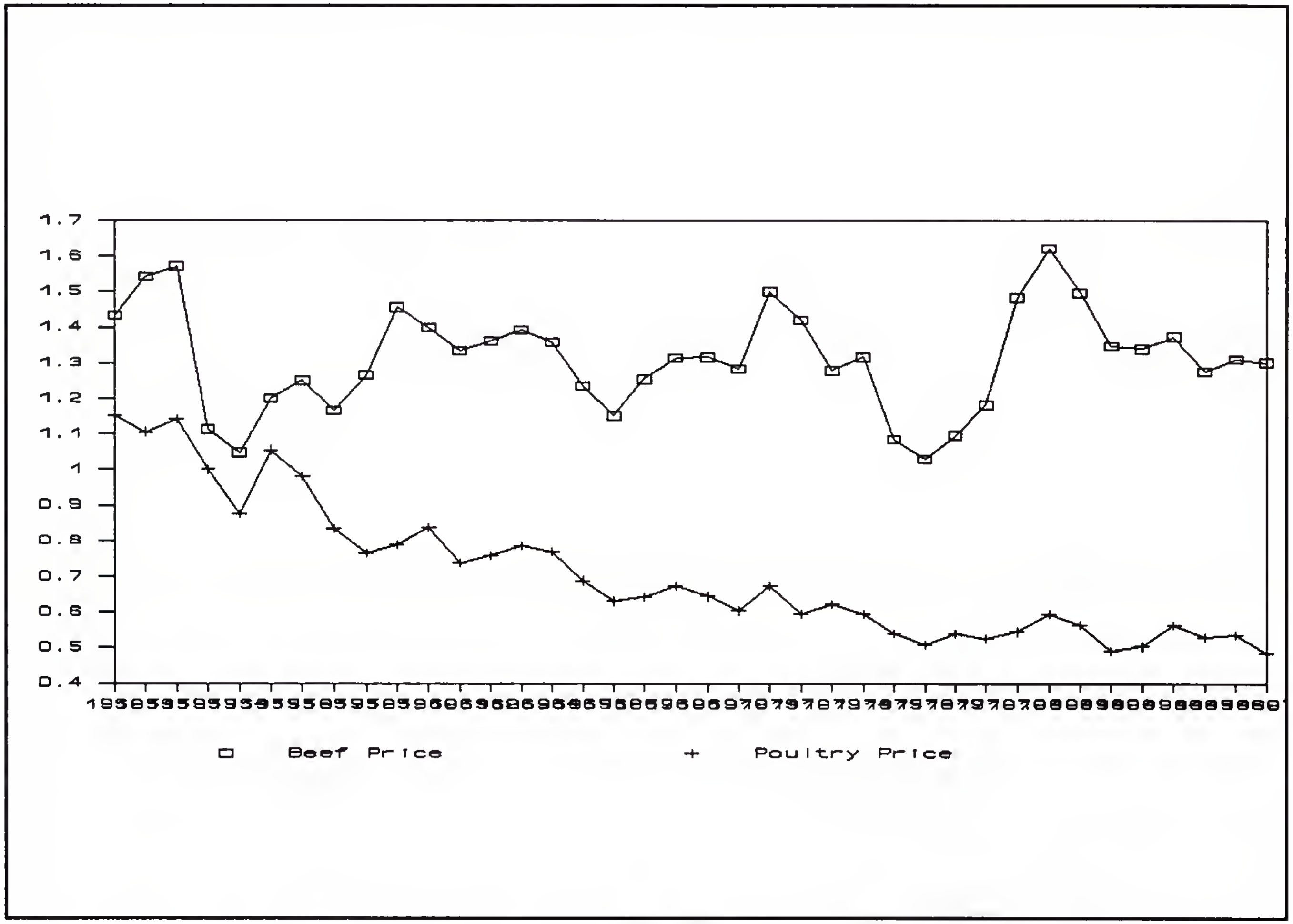

Figure 2. Nominal Retail Prices of Beef And Poultry Relative to Pork, 1950-1987.

CHAPTER 2
LITERATURE REVIEW

Many studies on the structural change of meat demand have been done, but different conclusions were drawn on the occurrence and timing of the structural change. When a demand system is estimated, it is usually assumed that factors not entering into the demand function remain constant throughout the data period of study. When any of the "constant" factors changes, the estimated demand function shifts, this is called structural change. In most meat demand models previously studied, the quantity or price is defined as a function of income and prices of related goods. Taste is assumed constant and not included in the demand model. When a shift is detected within the data period, it is then concluded that structural change has occurred and it is usually attributed to changing consumer tastes. Nyankori and Miller (1982), Braschler (1983), Chavas (1983), Thurman (1987), Eales and Unnevehr (1988), Moschini and Meilke (1989) present evidence that structural change occurred in meat demands in the 1970's, while studies by Haidacher et al. (1982), Moschini and Meilke (1984), Dahlgran (1987), and Chalfant and Alston (1988) found no such evidence. Most of the studies focused on the

red meat consumption. Only Thurman (1987) looked at poultry market demand closely. All the above studies except Chalfant and Alston (1988) estimated a demand system and inferred the occurrence and timing of structural change by identifying parameter changes.

All tests of structural changes were conducted with aggregate U.S. time series data. The diversity of empirical results may be due to a combination of factors, such as (1) the time span and the periodicity of data, (2) the number of parameters in the model, (3) the specification of gradual or abrupt change, (4) functional form, (5) price dependent versus quantity dependent specification, (6) the degree to which the theoretical structure is embodied in the empirical structure. Given the same data set, any of the above considerations may very well result in different structural change conclusions.

Studies by Chavas (1983), Frank (1984), and Moschini and Meilke (1984) attempted to capture the effect of all other prices by explicitly including a composite price index of all other commodities. The validity of this aggregate price index depends on the assumption that these prices change in proportion. This is a very restrictive assumption and rarely if ever satisfied. These studies usually rejected the inclusion of these price indexes in favor of a simpler version of model which excludes these indices.

Braschler (1982) and Leuthold and Nwagbo (1977) examined structural changes within single equation models by allowing abrupt change of parameters at a specific time. However, the point of structural change is usually identified by an ad hoc procedure. Even when some statistical methods are utilized for identifying these points, the same data are used again for testing, rendering this whole practice dependent on data mining. Leuthold and Nwagbo (1977) chose the midpoint of their relatively small 11-year sample of quarterly data as the point of structural change, and then examined the impact of changing that point by one year each time. They found no strong evidence of structural change during the 1964-75 period. Braschler (1983) used a price dependent, single equation model for beef and pork, finding evidence of structural change at the midpoint of his data set. He found that beef structural change occurred in 1971, pork in 1969. He found that pork prices are becoming less responsive to available quantities of pork and beef, more responsive to the quantity of broilers, and less responsive to changes in real income. For beef prices, he found that the response to the quantity of broilers changes from negative to positive, thus the increasing quantity of broiler consumption led to higher beef price. Increasing beef price is the result of increasing beef demand. This not consistent with his finding on the unfavorable structural changes against beef

demand. Although structural change can be elicited by many different methods, from an intuitive view, we would expect structural change to occur simultaneously in related commodities since they would all be affected by the same factors. We would expect the pork structural change to occur in the same year as the change in beef structure. Thus, while Braschler (1983) found a significant change in his empirical structure, his estimates of the demand structure are inconsistent with the assumed economic theory.

Frank (1984), Cornell and Sorenson (1986), and Dahlgran (1986) improved on some of the former studies in several ways. They employed statistical procedures that allow for gradual changes in parameters. Gradual changes are more plausible than abrupt changes in consumption behavior. It is compatible with habit formation and diffusion of information among consumers. Frank (1984) and Dahlgran (1986) also imposed restrictions that structural changes take place simultaneously among the meat commodities. Frank (1984) and Dahlgran (1986) found statistically significant evidence of parameter changes for beef, pork and chicken occurring around 1973-1975. Cornell and Sorenson (1986), using annual data for 1950-1982, found evidence of parameter changes for beef and broilers but not for pork.

Nyankori and Miller (1982), Chavas (1983), Thurman (1987), Moschini and Meilke (1984) used ad hoc demand functions to test the consistency of the structural change

hypothesis and data. The functions were usually defined in such a way that a quantity-dependent variable (per capita consumption of meat) was a function of consumer income and prices of related goods. Thurman (1987) did an endogeneity test and found that for poultry demand, price is predetermined by costs of production while quantity is determined by price. Dahlgran (1987), Eales and Unnevehr (1988), and Moschini and Meilke (1989) used complete demand systems. By way of specification, the allocation of expenditure for a group of meat commodities can be assumed to be independent of other commodities outside of this group.

The system of demand functions for these commodities should satisfy properties of adding-up, symmetry and homogeneity. It is a controversial issue that when using aggregate data these demand properties should still be satisfied. Christensen and Jorgenson and Lau (1975) rejected these demand properties using their now famous translog flexible function forms, and they concluded that the theory of demand is inconsistent with the evidence. Later studies by Simmons and Weiserbs (1979) showed that any flexible functional form is only an accurate local approximation to a true function. The estimated aggregate demand function will satisfy demand properties only when strict forms of individual preferences are assumed. Other studies obtained almost uniform rejection of demand

restrictions on aggregate data (Deaton and Muellbauer, pp. 74, 1980). Chalfant and Alston (1988) criticized these parametric functional form studies for failing to distinguish between the structural change and errors of specification in their parametric approach and proposed a non-parametric approach for assessing the structural change by using the Strong Axioms of Revealed Preferences (SARP).

Haidacher (1983) discussed the issues related to structural change in demand systems, particularly the issue of intractability of obtaining direct evidence on structural change via conventional procedures. He argued that since demand structure is uniquely determined by the utility function and the optimizing process, changes in structure must be a consequences of change in the utility function, U=F(q). Since the utility function is not directly observable, the change can only be reflected in the demand structure (which is unknown) and the observed behavior. Any observed behavior embodies two potential effects, response under a given structure and response from a changes in structure. If the specification of a given structure is not correct, the null hypothesis of linear demand structure with constant parameters that are invariant with respect to time would result in multiple alternative hypotheses rather than a single one. Each specification results in one more element in the alternative hypothesis set. Thus, the effort of obtaining direct evidence on structural change without

assurance of correct specification is futile. Haidacher proposed an indirect method to test structural changes which includes testing error of prediction and testing the constant term in an differential demand model. He strongly favored a complete demand system, arguing that it corresponds more closely to the classic optimizing model than most other specifications and provides the greatest potential for reducing the number of elements in the alternative hypothesis set due to specification error through omitted variables.

Chavas (1983) agreed that consumer concern regarding fat and cholesterol might have produced an important shift in meat preferences. This preference change can lead to permanent changes in behavioral relationships, and hence change the parameters in demand functions. He assumed that parameters can change randomly from one period to the next, and used the Kalman Filter specification to identify and estimate (update) parameter change in a linear demand model. The identification of the variance of these random elements is based on the minimization of a prediction error criterion. Application of the method to U.S. meat demand in the 1970s identified structural change to have occurred for beef and poultry, but not pork, in the last part of the decade. Chavas found that price and income elasticities of beef have been decreasing in the past few years, while the income elasticity of poultry has been increasing. This

analysis suggests that data before 1975 may not be very useful in measuring poultry and beef demand in the 1980s.

In a attempt to minimize the impact of specification error due to choice of functional form, Moschini and Meilke (1984) used the flexible Box-Cox transformation in a single-equation, quantity-dependent model of beef demand. They found no evidence of structural change over the period 1966-1981, but do find that price and income elasticities change with varying levels of prices and income. They correctly noted that such changes in response parameters do not necessarily imply structural change. They found that price elasticity of beef rises as the price of beef increases. This is plausible because demand would be more sensitive as this commodity becomes more expensive, as substitutes become more attractive. They found that income elasticity decreases as income increases, this is consistent with Engle's Law and the notion of a saturation point of food consumption.

Wohlgenant (1982,1986) attempted to explain the cause of structural change explicitly within the model specification. He found that parameter changes can be partially explained by quality changes in meats, which mainly are changes in protein, carbohydrates, iron, riboflavin, and ascorbic acid. He found that one-third of the unexplained decrease in demand for beef and pork and one-half of the unexplained increase in poultry are due to

quality changes in the respective products. The explained demand changes are defined as the variation not accounted by changes in income and prices. His model provides us some good insights into the casual factors influencing parameter changes.

Dahlgran (1987) used the Rotterdam model to test structural changes in meat demand, arguing that the Rotterdam model is derived from per capita demands rather than from representative consumer's preference, and that specification error is diminished by this model. Dahlgran assumed, based on the length of the gestation and production cycle for beef and pork and empirical evidence for chicken, that the annual supplies of beef, pork and chicken are fixed. This assumption dictates that meat quantities should be treated as given along with the prices of other foods and non-food items and that meat prices should be dependent variables. The time variant paths of the elasticities of meat demands show that significant changes in the demand system parameters were detected, and these changes were consistent with increased substitutability between beef and chicken. However, the timing and transitory nature of these changes does not support the contention of a permanent change in consumers' meat consumption preferences. Corresponding to the detected model parameter changes, the meat demand elasticity structure appeared to change substantially in the 1970s, but in the 1980s it has

restabilized. He concluded that the 1970s structure was an aberration and that the meat markets have since returned to an elasticity structure that is not very different from that displayed in the 1960s.

Eales and Unnevehr (1988) used two Dynamic Almost Ideal Demand Systems (DAIDS), one for aggregated meats and another for disaggregated meat products. Tests for weak separability show that consumers choose among meat products rather than meat aggregates such as "beef" and "chicken". Therefore, tests for structural change in the meat aggregates may be biased. They suggested that a full understanding of meat demand or tests for structural change require analysis of a disaggregated meat product model. Tests for structural change in disaggregated products revealed a different picture of preference changes than the aggregate model. Two types of significant shifts in meat demand were identified in meat products: an exogenous constant annual 6.4% growth in demand for chicken parts/processed from 1965 to 1985 and a 3.5% decline in demand for beef table cuts after 1974. Over the entire period, demand for whole birds declined slightly while demand for hamburger increased slightly. Growth in aggregate chicken is apparently due to growth in the demand for parts/processed. The model identified that hamburger and whole birds are inferior goods and chicken parts and beef table cuts are normal goods. Further findings of

disaggregate substitution made the authors refute the assumption that structural changes come from health concerns. They argued that a shift due purely to health concerns would have led to growth in whole birds and a decline in hamburger, but the contrary is true. While awareness of cholesterol may be greater among consumers of higher quality meats, the shift from beef table cuts to chicken parts/processed must also have been caused by growth in demand for convenience. They concluded that the chicken industry has responded to the increased demand for embodied service in chicken products by marketing new products. This suggests that the beef industry should develop new products to stimulate demand.

Moschini and Meilke (1989) tested the hypothesis of structural change in U.S. meat demand in a four-meat Almost Ideal Demand System with parameters following a gradual switching regression model. The results support the notion that structural change partly explains the observed U.S. meat consumption patterns. Structural change is significantly biased against beef, in favor of chicken and fish, and it is neutral for pork. Bias to structural change is attributed to changes in expenditure shares in this model when prices and expenditure are held constant. The estimated bias for beef implies that a decline of approximately 6 percent in beef share can be accounted for by the estimated changing structure at constant prices and

expenditures. One of the interesting conclusions of this study is that, contrary to other studies which reached similar conclusions about structural changes, the structural change did not significantly affect demand elasticities and elasticities of substitution.

Chalfant and Alston (1988) used a non-parametric approach to test structural changes in meat demand systems, arguing that the rejection of the stability hypothesis could well be due to use of the wrong functional form rather than a rejection of the economic proposition in parametric analysis. The advantage of the non-parametric approach is that it gives a test for stable preferences for market goods that does not require that they be of a particular form, such as AIDS. As in the parametric approach, the null hypothesis is that there is a stable set of preferences so that variation in observed quantities consumed can be explained by changes in relative prices or expenditures. When consumers obey the Strong Axiom of Revealed Preferences (SARP), there is a stable demand system that fully explains observed consumption patterns. This holds because the strong axiom is equivalent to the existence of a well-behaved utility function. The axiom does not need hold in the data when structural changes occur, so a test for violations of the axiom is capable of identifying changes in preferences. A check for consistency with the axioms of revealed preference, applied to the U.S. and Australian meat

data, showed that the data from both countries could have been generated by stable preferences. The overwhelming evidence of meat consumption changes may be attributed to the fact that household production functions have shifted over time and that meat is being perceived and used differently by consumers.

The problem with this non-parametric approach is the power of the test. When total expenditure is increasing over the sample period, the demand function (of latter time) would be pushed out to the right, possibly not intersecting with the comparison supply function (which is independent of consumer expenditure and should remain in the original position). When this occurs, no earlier consumption bundle can be revealed to be preferred to any subsequent bundle, as all subsequent bundles were unaffordable in the earlier period, and as a result the model tends to accept the null hypothesis more often than it should. The non-parametric model is more appropriate for cross sectional rather than time series analysis.

Choi and Sosin (1990) used a translog flexible functional form specification for the underlying indirect utility function to develop a demand function which has a smooth logistic function multiplicative term. This logistic multiplicative term is a function of time trend and represents smoothing change of tastes. Structural changes alter the marginal rates of substitution between goods at

fixed points of prices and quantities, and the multiplicative term. Their study found evidence of red meat demand structural changes in mid 1970's. The statistics of fit are also improved by defining an evolving multiplicative structural term in the demand function.

A summary of the studies on the structural change in retail meat demand is in appendix 1.

Other meat demand literature, although not directly related to the structural change studies, uses cross section data to analyze the effects of social-economic and demographic factors on preference formation. Heien and Pompelli (1988) used USDA 1977 Household Food Consumption Survey (HFCS) data, estimated an AIDS model for three major cuts of beef:steak, roast, and ground beef. They found the impact of certain demographic effects, such as household size, region, tenancy, and ethnic origin, was generally quite significant. Black and Hispanic households have higher preferences for steak and ground beef, but relatively low preferences for roast. Other demographic variables, such as employment status, shopper, and occupation, were generally not significant.

Jensen and Schroeter (1989) used household panel scanner data on fresh beef demand from a supermarket universal product code (UPC) scanner system. The product, price and quantity information for selected panelists' grocery shopping trips is read by scanners and used to

update computer-based purchase logs for each of a large number of participating households in a experimental market area. The extended period of experiment provided data for time-series and cross-section analysis. The Non-white ethnic group (eighty percent are Hispanic families in the sample) consume more fresh beef than white families. Households headed by a 45 to 64-year-old tend to consume significantly more beef than do otherwise comparable households headed by younger or older individuals. This perhaps is in accordance with other studies that found that grown children present in households headed by 45- to 64-year-olds eat more fresh beef than the younger children typically found in the households of younger parents. Households headed by a single female consume disproportionately less beef than do households with two heads. This finding is perhaps related with demand for convenience, single mother families usually face more demands for their time, and beef takes longer to cook. They also found that college-educated households purchase nearly .5 lb./month less fresh beef than do households with members who have no college experience. Families having higher education have easier access to information relating health concerns to food intake, and respond more quickly to this information.

Although the cross section studies can not address the question of preference change over years, they can lay the

theoretic foundation for time series analysis. This information can then be used for time series studies to asses the aggregation problem which researchers would inevitably encounter during their research.

CHAPTER 3
LATENT VARIABLE MODELS

A latent variable is a variable which is not observable. It is usually represented by a proxy when its presence is crucial to the model. Other names of latent variables include unobservable variables, errors of measurement, errors in the variables, and factors. Taste or consumer preference can be considered a latent variable. In this chapter, two approaches to estimating latent variable models are reviewed. The structural equation static latent variable model and state space dynamic latent variable model are used in Chapter 4 to estimate the latent taste variable.

Structural Equation Models

Goldberger (1972b) has a comprehensive review of the development of latent variable methods in econometrics. In the early days of econometrics, equations were formulated as exact relations among unobservable variables, and errors in the variables provided the only stochastic component in observations. The emphasis soon shifted entirely to errors in the equations since the days of the Cowels Commission. A possible justification for this neglect is that measurement errors in economic data are negligible, at least in

comparison to behavioral disturbance. However, the real explanation may have been the misconception that error in variable models are under-identified. This under-identification posed difficulty in estimation and testing, and presented a seeming impasse to econometricians at the time. In empirical econometrics it is often common to find "proxy" or "surrogate" variables used freely, with little effort made to trace out the consequences. It is often assumed that taste or preference is constant in maximizing utility functions, so demand functions compatible with this property of the utility function ignore the latent variable. When the model is applied to time series price and quantity data, where taste or preference may have changed over time, omitting taste change can render estimation inconsistent. More problematic is the approach to identifying structural (taste) change in such a model by using surrogate variables like residual autocorrelation, time trend dummy, etc. The specification error of omitting a latent variable in the original model setting along with other specification errors mentioned by Chalfant and Alston (1988) makes it impossible to identify structural change caused by taste change of consumers.

The effect of using a "proxy" instead of true variable in regression analysis can be demonstrated by the following model (Fuller, 1987). The classical linear regression model is defined by

$$Y_t = \beta x_t + e_t$$

and one is unable to observe x_t directly, only Z_t is observed directly.

$$Z_t = x_t + u_t \tag{3.1}$$

The regression coefficient ($\hat{\beta}$) computed from the observed variables is biased toward zero.

$$E\{\hat{\beta}\} = \sigma_{ZZ}^{-1}\sigma_{ZY} = \beta(\sigma_{xx} + \sigma_{uu})^{-1}\sigma_{xx}. \tag{3.2}$$

As σ_{uu} becomes greater, $(\sigma_{xx} + \sigma_{uu})^{-1}\sigma_{xx}$ tends to zero.

The latent variable model is usually discussed in the more general framework of structural equation models. The term "structural" stands for the assumption that each equation represents a causal link, rather than a mere empirical association. Structural equation models are regression equations with less restrictive assumptions that allow measurement error in the explanatory as well as the dependent variables. They routinely include multiple indicators of latent variables. These models encompass and extend path analysis, econometrics, and factor analysis. Unfortunately, they have only been widely used in other social sciences like sociology, psychology and political science.

Structural equation models have two major branches, path analysis and factor analysis, which are often used in sociology and psychology, respectively. Path analysis was invented by biometrician Sewall Wright in 1918. It has three aspects, a path diagram, the equation relating

correlations or covariances to parameters, and the decomposition of effects. The path diagram is a pictorial representation of a system of simultaneous relations. It shows relations between all variables, including disturbances and errors. The second aspect of path analysis sets up rules to write the equation that relates the covariance of variables to the model parameters. It basically is a moment estimator. The second moment of the sample data matrix is defined equal to a matrix of structural parameters. The unknown structural parameters are estimated by substituting sample covariance for the population covariance matrix and solving the above equality. The third aspect of path analysis provides a means to distinguish direct, indirect, and total effects of one variable on another. The direct effects are those not mediated by any other variables; the indirect effects operate at least through one intervening variable, and the total effect is the sum of direct and indirect effects.

Wright used his path analysis methods in many latent variable studies, such as bone size of rabbits, skin color of guinea pigs, and human intelligence. Wright also wrote an article in 1925 on estimating supply and demand functions simultaneously, using the path analysis method to address identification problems, long before economists had sufficient knowledge of this problem. Path analysis has been largely neglected by econometricians ever since its

birth. In the 1960s, sociologists began to realize the potential of path analysis and the related "partial correlation" techniques as a means to analyze non-experimental data. Many studies have been done to analyze latent variables like political stability, governing power, democracy, education, etc. In the 1970's, more general and elaborate matrix methods had developed and they incorporated path diagrams and other features of path analysis into their presentations. Path analysis has become more general and mathematically more elegant, the vocabulary of "covariance structural", "latent variable", "multiple indicators" has become commonplace in quantitative sociology.

Factor analysis also has a long history. It was invented by Spearman in 1904. It emphasizes the relation of latent factors to observable variables. Factor analysis has been used in psychology since the 1930's, especially in educational psychology. Unlike path analysis, factor analysis was looked at by economists briefly in 1970's, but the curiosity was soon dismissed as researchers might have confused factor analysis with principal component analysis which they view as a mechanical procedure for reducing dimensionality in regression computations. Even among the few who understood that factor analysis is more than a data management technique, the misconception of underidentification in the errors in variables model deterred many people. Goldberger (1972b) presented two

reasons that made factor analysis unattractive for econometricians: (1)economists are not attracted by models in which variables and parameters are redefined ex post, and (2) economists are not attracted by model in which all observable variables are treated symmetrically as effects of unobservable causes.

The structural equation model rapidly developed since the 1970's. It combined the newest improvement in both path analysis and factor analysis and has become a general approach to latent variable models. It includes path analysis, factor analysis and classical econometrics as a special cases. The observed variable can be causes or effects of latent variables, or observable variables can directly affect each other. This is an expansion of restrictive factor analysis where all indicators are viewed as effects of the latent variables. The work by Joreskog (1973) and Wiley (1973) completed the generalization of this model. This model had two parts. The first was a latent variable model that was similar to the simultaneous equation model of econometrics except that all variables were latent variables. The second part was the measurement model that showed indicators as effects of latent variables as in factor analysis.

The first component of structural equation system is a latent variable model (Bollen, pp.319-326, 1989):

$$\eta = B\eta + \Gamma\xi + \zeta \tag{3.3}$$

where, η (m×1) is the vector of latent endogenous random variables; ξ (n×1) is the vector of exogenous random variables; B is an m×m coefficient matrix showing the influence of latent endogenous variables on each other; Γ is the m×n coefficient matrix for the effects of ξ on η. The matrix (I-B) is assumed nonsingular. ζ is the disturbance vector that is assumed to have an expected value of zero and is uncorrelated with ξ. The second component of the structural equation model is the measurement model:

$$y = \Lambda_y \eta + \epsilon \qquad (3.4)$$

$$x = \Lambda_x \xi + \delta \qquad (3.5)$$

where the y (p×1) and the x (q×1) vectors are observed variables; they are also called indicators of latent variables η and ξ. The Λ_x and Λ_y are (p×m) and (q×n) coefficient matrices showing the relationship of latent variables to their indicators respectively. The ϵ (p×1) and δ (q×1) are the errors of measurement for y and x, respectively. The measurement errors are uncorrelated with latent variables, and have expected value of zero.

The equations (3.3), (3.4) and (3.5) are general form of structural equation models. It is clear that the classical econometric model is only a special case of this model where Λ_x and Λ_y are identity matrices and the covariance matrices of measurement errors θ_ϵ (p×p) and θ_δ (q×q) are zeroes. In this case, if $B \neq 0$, we have a simultaneous equation system.

$$y = By + \Gamma x + \zeta \tag{3.6}$$

The equation (3.5) represents a typical factor analysis model, a special case of the general set-up. The ordinary measurement error model, where endogenous and exogenous variables are measured with errors, is also a special case of the structural equation model, e.g.

$$\eta = B\eta + \Gamma\xi + \zeta \tag{3.7}$$

$$y = \eta + \epsilon \tag{3.8}$$

$$x = \xi + \delta \tag{3.9}$$

where $\Lambda_x = I_p$ and $\Lambda_y = I_q$ and the covariance matrices of measurement errors θ_ϵ and θ_δ are non-zero.

The estimation of the structural equation model is somewhat different than with the traditional econometrics approach. The latter derives from the minimization of the sum of squared differences of the predicted and observed dependent variables for each observation. The procedure used here emphasizes covariances rather than observations. Instead of minimizing the sum of squared differences of observed and predicted values, we minimize the difference between the sample covariances and the covariances predicted by the model. The fundamental hypothesis for these structural equation procedures is that the covariance matrix of the observed variables is a function of a set of parameters. This fundamental hypothesis is expressed as

$$S = \Sigma(\theta) \tag{3.10}$$

where S is the sample covariance matrix of observed

variables, θ is a vector that contains the model parameters, and $\Sigma(\theta)$ is the implied covariance matrix written as a function of θ.

Assuming we have an endogenous set y and an exogenous set x, the population covariance matrix for y and x is

$$\Sigma = \begin{bmatrix} VAR(y) & COV(x,y) \\ COV(y,x) & VAR(x) \end{bmatrix} \tag{3.11}$$

The implied covariance matrix $\Sigma(\theta)$ is the covariance matrix written as a function of the free model parameters in θ. It can be expressed like

$$\Sigma(\theta) = \begin{bmatrix} \Sigma_{yy}(\theta) & \Sigma_{xy}(\theta) \\ \Sigma_{xy}(\theta) & \Sigma_{xx}(\theta) \end{bmatrix} \tag{3.12}$$

where $\Sigma_{xy}(\theta) = E(xy')$. The exogenous and (or) endogenous variables x, y can be expressed as function(s) of the parameter vector θ, then, finally $\Sigma_{xy}(\theta) = E(xy') = f(\theta)$. In practice, the population covariances (Σ) or the parameters (θ) are both unknown, so S is used to substitute for Σ.

Define $\Sigma(\hat{\theta})$ to be the implied covariance matrix with estimated $\hat{\theta}$ replacing θ. The residual matrix $(S - \Sigma(\hat{\theta}))$ indicates how close $\Sigma(\hat{\theta})$ is to S. The unknown parameters can be estimated by minimizing residuals or a function of a residual matrix. This function (also called the fitting function), $F(S, \Sigma(\hat{\theta}))$, has the following properties: scalar, non-negativity, equals to zero only when $S = \Sigma(\hat{\theta})$, and continuous in S and $\Sigma(\hat{\theta})$. Minimization of fitting functions

satisfying these properties leads to consistent estimators of θ (Bollen, pp.106, 1989). There are a few such fitting functions. Maximum likelihood (ML) is the one proposed here.

The maximum likelihood method (ML) is the most widely used fitting function in general structural models. The fitting function that is minimized is

$$F_{ml} = T/2\log|\Sigma(\theta)| + T/2tr(S\,\Sigma^{-1}(\theta)) \qquad (3.13)$$

The derivation of F_{ml} is from the assumption that variables x and y are normally distributed, and the fundamental hypothesis $S = \Sigma(\theta)$ holds. If we combine y and x into a single $(p+q)\times 1$ vector z, for a random sample of T independent observations of z, its log likelihood function is (Bollen, 1989):

$$\log L(\theta) = \frac{-T(p+q)}{2}\ln(2\pi) - (T/2)\ln|\Sigma(\theta)| - (1/2)\sum_{i=1}^{T} z'_i \Sigma^{-1}(\theta) z_i \qquad (3.14)$$

The $\log L(\theta)$ and the negative F_{ml} are equivalent, the log likelihood is maximized when F_{ml} is minimized.

For the general structural equation models defined by (3.3)-(3.5), the elements of the implied covariance $\Sigma(\theta)$ are:

$$\Sigma_{xx}(\theta) = E\,(xx') = \Lambda_x\, \Phi\, \Lambda'_x + \Theta_\delta \qquad (3.15)$$

where Φ stands for the covariance matrix of latent variables ξ. The covariance of y can be written as a function of the unknown model parameters that are stacked in the vector, θ. The $\Sigma_{yy}(\theta)$ is

$$\Sigma_{yy}(\theta) = E(yy')$$
$$= E\,[(\Lambda_y\,\eta + \epsilon)(\Lambda_y\,\eta + \epsilon)']$$
$$= \Lambda_y E(\eta\eta')\Lambda'_y + \Theta_\epsilon \tag{3.16}$$

It can be further broken down by substituting the reduced form of equation (3.3), that is, $\eta = (I - B)^{-1}(\Gamma\xi + \zeta)$, in equation (3.16) and simplifying

$$\Sigma_{yy}(\theta) = \Lambda_y\,(I - B)^{-1}(\Gamma\Phi\Gamma' + \Psi)[(I - B)^{-1}]'\Lambda'_y + \Theta_\epsilon \tag{3.17}$$

where Ψ stands for the covariance matrix of errors in the equations ζ. Using similar argument, we have

$$\Sigma_{yx}(\theta) = E(yx')$$
$$= E\,[(\Lambda_y\,\eta + \epsilon)(\Lambda_x\,\xi + \delta)']$$
$$= \Lambda_y E(\eta\xi')\Lambda'_x$$
$$= \Lambda_y(I-B)^{-1}\Gamma\Phi\Lambda'_x \tag{3.18}$$

The implied covariance matrix of the general structural equation (3.12) is

$$\Sigma(\theta) = \begin{bmatrix} \Lambda_y(1-B)^{-1}(\Gamma\Phi\Gamma'+\Psi)[(I-B)^{-1}]'/\Lambda'_y + \Theta_\epsilon & \Lambda_y(I-B)^{-1}\Gamma\Phi\Lambda'_x \\ \Lambda_x\Phi\Gamma'[(I-B)^{-1}]'\Lambda'_y & \Lambda_x\Phi\Lambda'_x + \Theta_\delta \end{bmatrix} \tag{3.19}$$

The classical econometric regression model is a special case of this general expression when latent variables are measured without error. The least square estimator is equivalent to the above estimator when all variables are observable. Suppose the linear regression model is expressed as

$$y = \Gamma x + \zeta \tag{3.20}$$

where both the variables x and y are observable. The implied covariance matrix for this regression model is

$$\Sigma(\theta) = \begin{bmatrix} \Gamma\Phi\Gamma'+\Psi & \Gamma\Phi \\ \Phi\Gamma' & \Phi \end{bmatrix} \tag{3.21}$$

This is a special case of (3.19) when $\Lambda_x=\Lambda_y=I$, and $\Theta_\epsilon=\Theta_\delta=0$. We want the sample covariance matrix to be equal to the implied covariance matrix

$$\begin{bmatrix} VAR(y) & COV(x,y) \\ COV(y,x) & VAR(x) \end{bmatrix} = \begin{bmatrix} \Gamma\Phi\Gamma'+\Psi & \Gamma\Phi \\ \Phi\Gamma' & \Phi \end{bmatrix} \tag{3.22}$$

then $COV(x,y) = \Gamma\Phi = \Gamma\ VAR(x)$, $\Gamma = COV(x,y)/COV(x)$. This is the same as the conventional Least Square estimator.

The Multiple-indicator and Multiple-cause (MIMIC) model originally formulated by Zellner (1970) and then extended by Goldberger (1972, 1977) is a special case of the general latent variable model when latent variable ξ is observable. The latent variable η has indicators y, and itself is a function of cause variable x.

$$\eta = B\eta + \Gamma x + \zeta \tag{3.23}$$

$$y = \Lambda_y\ \eta + \epsilon \tag{3.24}$$

It is not enough to estimate the coefficients of the latent variable only, sometimes it is necessary to estimate the latent variable itself. This is done by a GLS estimator which uses estimated latent variable coefficients. For instance, the latent taste variable ξ can be calculated by estimating a GLS model if only (3.3) is considered (Fuller 1987, Shonkwiler and Ford 1989).

$$(I - \hat{B})Y = \hat{\Gamma}\xi + \zeta \tag{3.25}$$

$$\hat{\xi} = (\hat{\Gamma}'\hat{\Psi}^{-1}\hat{\Gamma})^{-1}\hat{\Gamma}'\hat{X}^{-1}(1-\hat{B})Y \tag{3.26}$$

State Space Model

Another way to estimate the time variant taste variable is to use state space form. This is a term widely used in engineering literature for describing a system in which parameters follow a dynamic path. State form is often solved by a filtering method, and is sometimes called the Kalman filter. The fact that state space form techniques provide an ideal framework for estimating equations with latent variables has been increasingly recognized by economists, see Harvey and Phillips (1979), Pagan (1980), Engle and Watson (1981,1985), Engle et al (1985), Burmeister and Wall (1987), Slade (1989). The specification is as follows:

$$Y_t = B\Xi_t + \Gamma X_t + e_t \tag{3.27}$$

$$\Xi_t = \Phi\ \Xi_{t-1} + \delta F_t + \mu_t \tag{3.28}$$

Equations (3.27) are the measurement equations, where Y_t is a (n×1) vector of observations on n dependent variables, B is a fixed matrix of order (n×j), and Ξ_t is an j×1 vector of unobserved state variables. X_t is a (n×k) matrix of observable variables with the parameter vector Γ, etc. Equations (3.28) are the transition equations for the state variables, with Φ a fixed matrix of order j×j, F_t is an (j×m) matrix of observations on m nonstochastic variables,

and δ is an (m×1) coefficient vector. Latent variables can be included in the state variable vector Ξ. e_t and μ_t are normal disturbance vectors with zero means and covariance matrices Ω_e and Ω_μ, respectively. e_t and μ_t are assumed to be serially uncorrelated, uncorrelated with each other for all t and uncorrelated with Ξ_0.

For $\Omega_\mu \neq 0$, the parameter vector is random. Similarly, for $\Phi \neq 1$ or $F_t \neq 0$, we have systematic parameter variation. If $\hat{\Xi}_t$ is the estimate of Ξ_t using observations through t and Σ_t is the covariance matrix of $\hat{\Xi}_t$, Kalman filtering gives the following sequential estimator of Ξ_t in the model of equations (3.27) and (3.28)

$$\hat{\Xi}_t = \hat{\Xi}_{t/t-1} + G_t[Y_t - B_t\hat{\Xi}_{t/t-1} - x_t\Gamma] \tag{3.29}$$

with covariance matrix

$$\Sigma_t = \Sigma_{t/t-1} - G_tB_t\Sigma_{t/t-1} \tag{3.30}$$

where G_t is the gain of the filter, $\hat{\Xi}_{t/t-1}$ and $\Sigma_{t/t-1}$ are prior estimators of state variables and their covariance matrix, respectively. They are defined as

$$G_t = \Sigma_{t/t-1}B'_t[B_t\ \Sigma_{t/t-1}B'_t + \Omega_e]^{-1} \tag{3.31}$$

$$\hat{\Xi}_{t/t-1} = \Phi\ \hat{\Xi}_{t-1} + F_t\delta_t \tag{3.32}$$

$$\Sigma_{t/t-1} = \Phi_t\Sigma_{t-1}\Phi'_t + \Omega_\mu \tag{3.33}$$

The prior estimators are the predictions of period t using actual information available in period t-1. The posterior estimate of Ξ_t, given in (3.29), is simply the prior estimate of $\hat{\Xi}_{t/t-1}$, plus the prediction error (Y_t - $B_t\hat{\Xi}_{t/t-1}$) weighted by the gain of the filter. The gain of the

filter can be shown to be the coefficient of the least squares regression of Ξ_t on the prediction error $(Y_t - B_t\hat{\Xi}_{t/t-1})$, conditional on Y_{t-1} (Meinhold and Singpurwalla, 1983). Similarly, the posterior variance Σ_t in (3.30) is the prior variance $\Sigma_{t/t-1}$ minus the positive semi-definite matrix $G_tB_t\Sigma_{t/t-1}$. If the parameters of equation (3.30) are known, then the estimator in (3.29) gives the minimum variance, unbiased estimator of Ξ_t.

The aim of filtering is to find the expected value of the state vector Ξ_t conditional on the information available at time t, that is $E(\Xi_t/Y_t)$. The aim of smoothing is to take account of the information made available after time t. The mean of the distribution of Ξ_t, conditional on all the sample, may be written as $E(\Xi_t/Y_T)$ and is known as a smoothed estimator. Since the smoothed estimator is based on more information than the filtered estimator, it generally will have a MSE smaller than that of the filtered estimator.

The fixed interval smoothing algorithm used in this study consists of a set of recursions which start with the final quantities, Ξ_T and Σ_T, given by the Kalman filter and work backwards. The equations are

$$\Xi_{t/T} = \Xi_t + \Sigma_t^*(\Xi_{t+1/T} - \Phi_{t+1}\Xi_t) \qquad (3.34)$$

$$\Sigma_{t/T} = \Sigma_t + \Sigma_t^*(\Sigma_{t+1/T} - \Sigma_{t+1/t})\Sigma_t^* \qquad (3.35)$$

where

$$\Sigma_t^* = \Sigma_t\Phi'_{t+1}\Sigma^{-1}_{t+1/t}, \quad t=T-1,\ldots 1 \qquad (3.36)$$

with $\Xi_{T/T} = \Xi_T$ and $\Sigma_{T/T} = \Sigma_T$.

As shown in Harvey (1989) the likelihood function of the unknown parameters in (3.27)-(3.28) is easily formed. Let η_t denote the innovations in y_t, $y_t - E(y_t/y_{t-1},...,y_1, z_t,...,z_1)$; and let G_t denote the variance of η_t. the log likelihood can be written as

$$L(\theta) = \text{constant} -1/2 \sum_{t=1}^{t} (\log|G_t| + \eta'_t G_t^{-1} \eta_t) \qquad (3.37)$$

where θ is the vector of unknown parameters. The innovations and their variances are easily calculated using the Kalman filter. Note that the innovation variance is equal to the gain of Kalman filter G_t.

The state space model of (3.27)-(3.28) can be estimated by using the EM methods suggested by Watson and Engle (1983). This technique was originally developed by Dempster et al (1977) for maximizing a likelihood function in the presence of missing observations. It consists of two steps: an estimation and a maximization step which are iterated to convergence. The maximization step calculates the maximum likelihood estimates of all the unknown parameters conditional on a full data set. The estimation step constructs estimates of the sufficient statistics of the problem conditional on the observed data and the parameters. In the state space model, the unobservables are treated just like missing observations. The estimation step consists of a Kalman filter smoother which gives sufficient statistics

of the latent variable. When the latent variable is estimated, the maximum likelihood estimates could then be calculated by forming the appropriate sample moment matrices necessary for the multivariate regression problem. Putting these two steps together, we have an algorithm. From an initial guess of the parameters we use a Kalman filter and smoother, a signal extraction procedure, to estimate the latent variable(s) and its variance. Combining these with the observed data we form the appropriate moment matrices and obtain new parameters using standard regression formulae. These new parameter estimates are used to form new estimates of the latent variable(s), and the procedure is repeated until convergence.

The Kalman filter requires a value of the mean and variance of Ξ_0 as an initialization. When these starting values are not known, they must be constructed. Different methods should be used depending on whether the stochastic process generating Ξ_t is stationary. When Ξ_t is stationary, as is the case here, starting values can be computed from the first J observations by setting $\Xi_{0/0}=0$ and $\Sigma_{0/0}=\kappa I$, where κ is a large scaler.

Upon convergence of the estimation algorithm, the Kalman smoother can be run to obtain an estimate of the prior conditioned on the parameter estimates. With the prior estimate so obtained, the estimation and smoothing process is repeated until both constant parameters and

priors match. In any case, the initial value will not affect the estimation of state variables when the sample is large (Watson, 1983).

The EM method is an iterative two step method, it is better than some other state space estimators such as the Scoring method (Pagan, 1980). This maximizes the state space likelihood (3.37), with respect to all latent variables as well as parameters, using numerical derivatives for the score and information matrix. It is equivalent to recursively substituting the transition equation into the measurement equation, and maximizing the likelihood function of the reduced function.

CHAPTER 4
MODEL SPECIFICATION

As reviewed in the previous section, economists are traditionally suspicious of latent variables. More so in the case of applied consumption analysis perhaps because " a profession's intellectual tastes change slowly" (Pollak, 1978). Nevertheless it is time to reconsider some of the old wisdom toward taste formation and taste change.

Among those who are suspicious or pessimistic of taste modeling are some of the best known economists such as Milton Friedman and George Stigler. Friedman (1962) writes:

> Despite these qualifications, economic theory proceeds largely to take wants as fixed. This is primarily a case of division of labor. The economist has little to say about the formation of wants; this is the province of the psychologists. The economist's task is to trace the consequences of any given set of wants. The legitimacy of and justification for this abstraction must rest ultimately, in this case as with any other abstraction, on the light that is shed and the power to predict that is yielded by the abstraction. (p.13)

It is perhaps reasonable to argue that it is the psychologist's work to figure out how the taste change takes place. However, just as Friedman emphasizes the proper test of validity of this division of labor is its power to predict, the current need to estimate taste formation and taste change has largely come from empirical demand analysis, like meat demand analysis. The taste (structural)

change makes many econometric models which used pre-change data perform poorly in prediction in recent years (Purcell, 1989). The declining predictive power of meat models suggests the inclusion of a taste variable in these models to improve their performance.

Stigler and Becker (1977) used household production theory to establish theoretically that taste can be treated as stable over time and among people. This is done by translating "unstable tastes" into variables in the household production function for commodities. By specifying demand models this way, all changes in behavior are explained by changes in prices and incomes. The household production theory assumes that the ultimate objectives of choice are commodities produced by each household with market goods, own time, knowledge and perhaps other inputs. Knowledge, for instance, can be produced by advertising and health information. An increase in advertising may lower the shadow prices of a commodity to the household and thereby increase its demand for the market output, because the household is made to believe - correctly or incorrectly - that it gets a greater output of the commodity from a given input of the advertised product. Consequently, advertising affects consumption in this formulation not by changing taste, but by changing shadow prices. That is, a movement along a stable demand curve for household produced commodities is seen as generating the

apparently unstable demand curves of market goods and other inputs. The change of demands for household produced commodities are independent of taste changes, taste change will not shift demand function for household produced goods. Taste changes will only be able to change the shadow prices of the household produced commodities. Household production theory is difficult to implement empirically. In this study we will estimate demand functions in market goods space. In this case the taste variable would enter into the demand equation directly.

There are a number of ways to incorporate taste formation into the analysis of household behavior. Some of the methods of incorporating advertisement effects into demand models can be used here (Green 1985, Brown and Lee 1989). Advertisement and taste are related latent variables, the former affects the latter. The traditional utility function assumes that consumer tastes are constant. To extend the traditional demand model to include tastes, the assumption of constant taste must first be relaxed. The general consumer preference choice can, in general, be written as (Grandmont, 1983)

$$\text{Maximize } u=u(q, \Xi) \qquad (4.1)$$

$$\text{subject to } p'q = x$$

where q and p are n×1 vectors of quantities and prices respectively. x is total expenditure or income. The latent variable Ξ can be a single measure of taste , or more

generally a vector of taste measures for commodities. In this study, one taste measure will be used for all meat products based on the assumption that health concern is the major factor of changing tastes, and it influences all meat demands. However the following discussion may be generalized to include other measures, such as advertising and convenience.

The demand equations found by solving (4.1) have the general form

$$q_i = f_i(p,\ x,\ \Xi) \tag{4.2}$$

The indirect utility function and cost function for problem (4.2) can be written as

$$u = g(p,\ x,\ \Xi) \tag{4.3}$$

$$x = c(p,\ u,\ \Xi) \tag{4.4}$$

respectively. Equation (4.3) can be derived from (4.4) using Roy's identity. The compensated demand equation is the first derivative of the cost function (4.4) using Shepard's lemma

$$h_i(p,\ u,\ \Xi) = \frac{\partial c}{\partial p_i} \tag{4.5}$$

The direct approach of allowing taste variables to appear in the utility (and cost) function generating a viable demand system is used in this study. A theoretically plausible demand system, the almost ideal demand system (AIDS) of Deaton Muellbauer (1980), will serve as the basic specification. The AIDS model was chosen because of the six

desirable properties mentioned by Deaton and Muellbauer (1980). In addition, it allows for consistent aggregation across consumers. The AIDS permits individual demand function restrictions to hold for aggregate or market demand functions (Green, 1985). Finally, the AIDS possesses desirable properties with respect to how income and price elasticity vary over time (Blanciforti and Green, 1983). The AIDS satisfies two of the most important prerequisites of incorporating taste effects into a demand system. First, the starting function must be general enough to act as a second-order (or first-order) approximation to any arbitrary direct or indirect utility function, cost function, or demand function. It would be ideal if it is a flexible functional form and be consistent with axioms of choice. The flexible functional cost form of the AIDS can satisfy the theoretical properties of concavity, homogeneity, continuity, positivity, etc. Second, the derived demand functions must permit the testing of symmetry, homogeneity, and adding-up. The methods of translating will allow the incorporation of a latent taste variable into the demand model and still satisfy all the requisite proprieties (Green 1985, Brown and Lee 1989).

The translating approach is a technique used in demand analysis to include household composition and habit formation, which assumes that taste change results in demand change through income effect. It has the form

$$q_i = r_i + q_i^*(p,\ x^*) \qquad (4.6)$$

where x^* is equivalent to a supernumerary income and r_i is a function of the taste variable Ξ. Translating "allows necessary or subsistence parameters of a demand system to depend on the demographic variables" (Pollak and Wales, 1981). Rossi (1988) simplified the budget share translating in AIDS by allowing the aggregate expenditure shares to depend on a household characteristics factor, which augments the intercepts of ordinary demand curves, and in this study is represented by a latent preference shifter Ξ.

The AIDS approximates an arbitrary expenditure or cost function. The cost function is sufficiently flexible so that at any single point, all of its first and second derivatives with respect to prices and utility can be set equal to these of an arbitrary cost function. Deaton and Muellbauer specified the AIDS cost function as

$$\ln c(u,p)=\alpha_0+\sum_k\alpha_k \ln p_k+1/2\sum_k\sum_i\tau_{ki}\ln p_k \ln p_i+u\beta_0\prod p_k^{\beta k}+\Xi \qquad (4.7)$$

The demand equations are generated from this cost function using Shephard's lemma:

$$w_i = \partial \ln c/\partial \ln p_i \qquad (4.8)$$

This AIDS model with latent preference variable is called (LAT/AIDS) through this dissertation:

$$w_i = \alpha_i + \sum_j \tau_{ij}\ln p_j + \beta_i \ln[x/p^*] + \phi_i\Xi + \zeta_i \qquad (4.9)$$

where x is total expenditure on the group of goods being

analyzed, p_j is the price of the jth good within the group, p^* is the price index for the group, w_i is the share of total expenditure allocated to the ith good (i.e. $w_i = p_i q_i / x$), and the price index is approximated by the Stone index:

$$\ln p^* = \Sigma\, w_k \ln p_k. \tag{4.10}$$

The adding-up, homogeneity, and symmetry conditions hold (4.11-13), respectively, if

$$\sum_i \alpha_i = 1,\ \sum_i \tau_{ij} = 0,\ \sum_i \beta_i = 0 \text{ and } \sum_i \phi_i = 0 \tag{4.11}$$

$$\sum_j \tau_{ij} = 0, \text{ and} \tag{4.12}$$

$$\tau_{ij} = \tau_{ji} \tag{4.13}$$

because adding-up (4.11) holds, then if symmetry holds, homogeneity follows. The symmetry condition implies that the compensated cross price elasticities are equal; homogeneity condition means that consumer purchases will remain the same if good prices and income change by the same percentages, in other words, there is no "money illusion".

A general definition of the uncompensated elasticities of demand from the AIDS is

$$\begin{aligned} \epsilon_{ij} &= d\ln q_i / d\ln p_j \\ &= -\delta_{ij} + d\ln w_i / d\ln p_j \\ &= -\delta_{ij} + \{\tau_{ij} - \beta_i\ (d\ln p^* / d\ln p_j)\} / w_i, \end{aligned} \tag{4.14}$$

where these elasticities refer to allocations within the group holding constant total group expenditures (x) and all other prices (p_k, $k \neq j$), δ_{ij} is the Kronecker delta ($\delta_{ij} = 1$

for i=j; $\delta_{ij} = 0$ for $i \neq j$). The uncompensated price elasticities using the Stone index for approximating a price index are (Green and Alston, 1990)

$$\epsilon_{ij} = -\delta_{ij} + \tau_{ij}/w_i - \beta_i/w_i \{w_j + \sum_k w_k \ln p_k(\epsilon_{kj} + \delta_{kj})\} \quad (4.15)$$

The price elasticities can be obtained by solving a simultaneous equation system. A more widely used approximation is to assume that expenditure shares are constant, $d\ln p^*/d\ln p_j = w_j$, then,

$$\epsilon_{ij} = -\delta_{ij} + \{\tau_{ij} - \beta_i w_j\}/w_i \quad (4.16)$$

The expressions for the income and taste elasticities for LAT/AIDS are given, respectively, by

$$\mu_i = 1 + \beta_i/w_i \quad (4.17)$$

$$\epsilon_{i\Xi} = \phi_i \Xi\ /w_i \quad (4.18)$$

The expression (4.18) gives the taste effects on changing demand. It represents the percentage change in the quantity demanded of the ith commodity with respect to a percentage change in the taste index. This is the primary index that we are looking for in this study.

Several shortcomings related with the above latent variable specification and AIDS model should be kept in mind when we do the further estimation. In the context of a random objective function, e.g. cost and indirect utility functions, where the error terms are interpreted as unobservable factors or measurement errors associated with the indirect objective function, additive disturbances in the share equations may be heteroskedastic. In the AIDS

model the existence of heteroskedacity could lead to biased hypothesis testing (Chavas and Segerson, 1987). But when the unobservable variables are directly incorporated into the AIDS model, the effect would be similar to a weighted least square estimates applying to a linear regression model, the disturbance term will therefore less likely be heteroskedastic. The LAT/AIDS model in equation (4.9) assumes that the representative consumer receives information about health concerns instantaneously. This assumption can be relaxed by letting the latent taste variable follow a diffusing path. In a simple "epidemic model" new information is transferred to consumers either via other consumers or via the mass media. The probability of a representative consumer receiving the information may be represented by draw from a binomial distribution (Putler, 1988). Another simple way to model the slow adjustment of consumer taste change is to make the taste variable follow an auto-regressive path. Although the AIDS model is a flexible functional form, it can impose serious restrictions on the behavior of own and income elasticities. The demand for food becomes more inelastic with respect to price as real income rises (Wohlgenant, 1984).

The Rotterdam model (Theil, 1965) is another demand system which can be used as a framework for latent taste analysis. It is a differential demand model and is not based on a particular utility or cost function, but more

generally, on a first order approximation to the demand function themselves. The total differential of the demand equation $q_i=f(p_1,p_2,..p_n,x)$ is

$$dq_i = \frac{\partial q_i}{\partial x} dx + \sum_{j=1}^{n} \frac{\partial q_i}{\partial p_j} dp_1 , \qquad (4.19)$$

This can be transformed into a log form and have a additive taste variable term. The right hand side of the Rotterdam model is similar to the same as first difference form of the AIDS right hand side. It is expressed as (LAT/Rotterdam)

$$w_i \; \Delta \ln q_i = \sum_j \tau_{ij} \Delta \ln p_j + \beta_i \sum_k w_k \; \Delta \ln q_k + \phi_i \Delta \ln \Xi + e_i \qquad (4.20)$$

where expenditure and prices elasticities are

$$\mu_i = \beta_i / w_i \qquad (4.21)$$

$$\epsilon_{ij} = \tau_{ij}/w_i - \mu_i w_j \qquad (4.22)$$

Previous studies using Rotterdam model have shown that it is a good demand model with negligible approximation errors. It is linear in parameters and possesses unusually informative parameters. Although it is not a flexible functional form, its performance may not be inferior to the much more complicated, non-linear flexible functional forms.

Multiple Indicator Model

The multiple indicator model is a special case of general latent variable model outlined in Chapter 3:

$$\eta = B\eta + \Gamma\xi + \zeta \qquad (4.23)$$

$$y = \eta \qquad (4.24)$$

$$x = \Lambda_x \; \xi + \delta \qquad (4.25)$$

where only one variable is measured with error, and it is measured by several indicators.

The two indicators of the latent taste variable are a ratio of low fat milk consumption relative to whole milk consumption ("MILK") and a cholesterol index ("CHOLE"). The trends of the two indicators may represent how consumers are altering consumption patterns because of health concerns. The milk ratio is increasing because consumers buy more low fat milk due to concerns about the link of food fat and cholesterol intake to heart disease. Another indicator is the cholesterol index which measures the development and spread of health information linking fat intake and heart disease. The cholesterol index is from Brown and Schrader (1990), which is based on the number of citations of the link between cholesterol and arterial disease in medical journals. It represents the spread of information on cholesterol information to consumers and used in this model to indicate the speed of taste change adjustment.

For the case of LAT/AIDS model, assume, $B = 0$, $\lambda_y = I$, $\epsilon = 0$; other variables are

$$y = [\ w_1\ w_2\ w_3\ ]'$$

$$\xi = [\ln p_1\ \ln p_2\ \ln p_3\ \ln(x/p^*)\ \Xi\ ]'$$

$$x = [\ln p_1\ \ln p_2\ \ln p_3\ \ln(x/p^*)\ \text{MILK CHOLE}\ ]'.$$

In order to make the notation uniform throughout this dissertation, the general multiple indicator models in equation (4.23)-(4.25) will be presented in the framework

and using same notation as LAT/AIDS (4.9) and LAT/Rotterdam (4.20). The LAT/AIDS model is given below:

$$w_1 = \tau_{11}\ln p_1+\tau_{12}\ln p_2+\tau_{13}\ln p_3+\beta_1\ln(x/p^*)+\phi_1\Xi+\zeta_1 \qquad (4.26)$$

$$w_2 = \tau_{21}\ln p_1+\tau_{22}\ln p_2+\tau_{23}\ln p_3+\beta_2\ln(x/p^*)+\phi_2\Xi+\zeta_2 \qquad (4.27)$$

$$w_3 = \tau_{31}\ln p_1+\tau_{32}\ln p_2+\tau_{33}\ln p_3+\beta_3\ln(x/p^*)+\phi_3\Xi+\zeta_3 \qquad (4.28)$$

$$\text{MILK} = \Lambda_{x51}\Xi + \delta_1 \qquad (4.29)$$

$$\text{CHOLE} = \Lambda_{x61}\Xi + \delta_2 \qquad (4.30)$$

where $var(\zeta)=\Psi$, $var(\delta)=\Theta_\delta$.

The nature of share equations (adding-up) makes the LAT/AIDS model residual covariance matrix singular, so one of the equation is dropped arbitrarily. Since the system is estimated by ML, results are invariant to the equation dropped. This equation is then estimated with one of the first two equations again. The intercepts are eliminated by subtracting the means from each variable. In this case, the difference of original latent variable with its mean, $(\Xi-\bar{\Xi})$, enters into the latent variable equation and measurement equations. To make the model identifiable, some constraints are introduced to provide a scale for the latent variable. The latent preference variable, in this case, would have the same scale as the first indicator, low fat milk ratio. This translates to, Λ_{x51} being equal to one.

The implied covariance matrix for this structural equation model is

$$\Sigma(\theta) = \begin{bmatrix} (\Gamma\Phi\Gamma' + \Psi) & \Gamma\Phi\Lambda'_x \\ \Lambda_x\Phi\Gamma' & \Lambda_x \Phi \Lambda'_x + \Theta_\delta \end{bmatrix} \qquad (4.31)$$

The variables of LAT/Rotterdam model specification are expressed as

$$y = [\ w_1\Delta \ln q_i\ \ w_2\Delta \ln q_2\ \ w_3\Delta \ln q_3\ ]'$$

$$\xi = [\Delta \ln p_1\ \ \Delta \ln p_2\ \ \Delta \ln p_3\ \ \Sigma w_k\Delta \ln q_k\ \ \ln \Xi\ ]'$$

$$x = [\Delta \ln p_1\ \ \Delta \ln p_2\ \ \Delta \ln p_3\ \ \Sigma w_k\Delta \ln q_k\ \ MILK\ \ CHOLE\ ]',$$

using the same variable definitions as in the expressions presented above for the LAT/AIDS multiple indicator model. The LAT/Rotterdam equations are given below:

$$w_1\Delta \ln q_1 = \tau_{11}\Delta \ln p_1+\tau_{12}\Delta \ln p_2+\tau_{13}\Delta \ln p_3+\beta_1\Delta\Sigma w_k\Delta \ln q_k+\phi_1\Delta \ln \Xi+\zeta_1 \quad (4.32)$$

$$w_2\Delta \ln q_2 = \tau_{21}\Delta \ln p_1+\tau_{22}\Delta \ln p_2+\tau_{23}\Delta \ln p_3+\beta_2\Delta\Sigma w_k\Delta \ln q_k+\phi_2\Delta \ln \Xi+\zeta_2 \quad (4.33)$$

$$w_3\Delta \ln q_3 = \tau_{31}\Delta \ln p_1+\tau_{32}\Delta \ln p_2+\tau_{33}\Delta \ln p_3+\beta_3\Delta\Sigma w_k\Delta \ln q_k+\phi_3\Delta \ln \Xi+\zeta_3 \quad (4.34)$$

$$\Delta MILK = \Lambda_{x51}\ \Delta \ln \Xi\ +\delta_1 \quad (4.35)$$

$$\Delta CHOLE = \Lambda_{x61}\Delta \ln \Xi\ +\delta_2 \quad (4.36)$$

where var(ζ)=Ψ, var(ζ)=Θ, and Λ_{x51}=1.

Multiple Indicator Multiple Cause Model

The MIMIC model (3.23-3.24) is based on the argument that not only do the latent variables have indicators, they also have a causal relationship expressing them as a function of some cause variables. In this model, another factor affecting consumer taste change is augmented into the model. Taste change is assumed to be affected by both health concerns and demand for convenience goods. It is argued by some researchers that a higher proportion of working women in the population has increased household

demand for easy-to-cook meat such as chicken. The latent taste variable in the demand system, which is not measurable, has two indicators; they are the ratio of low fat milk ("MILK") and per capita consumption of eggs ("EGG"). The trends of the two indicators represent the results of consumer taste change because of health concerns. The milk ratio is increasing because consumers buy more low fat milk; while egg consumption is decreasing because of health concerns and the demand for convenience at the breakfast meal (Putler 1989, Shonkwiler and Ford 1989, Brown and Schrader 1990). In this model, the inverse of egg consumption is used to make it an increasing series compatible with the milk ratio indicator. The latent preference variable is influenced by two cause variables: the cholesterol information index ("CHOLE") and the percentage of married working women ("WOM"). The cholesterol index serves as a cause variable in this set-up based on our belief that the link of cholesterol intake and heart disease is arousing consumer concerns and therefore changing consumer tastes. The working women percentage represents changes in the family structure and shows the demand for convenience food.

The latent variable almost ideal demand system (LAT/AIDS) of equation (4.9) can be expressed within the framework of the MIMIC structural equation model (3.23)-(3.24) with the following specifications (when the third

share equation is dropped):

η = [Ξ w_1 w_2]'

y = [MILK 1/EGG w_1 w_2]'

x = [CHOLE WOM $\ln p_1$ $\ln p_2$ $\ln p_3$ $\ln(x/p^*)$]'

then for the latent equation part

$$\Xi_1 = \Gamma_{11}CHOLE + \Gamma_{12}WOM + \zeta_1 \tag{4.37}$$

$$w_2 = B_{21}\Xi + \Gamma_{23}\ln p_1 + \Gamma_{24}\ln p_2 + \Gamma_{25}\ln p_3 + \Gamma_{26}\ln(x/p^*) + \zeta_2 \tag{4.38}$$

$$w_3 = B_{31}\Xi + \Gamma_{33}\ln p_1 + \Gamma_{34}\ln p_2 + \Gamma_{35}\ln p_3 + \Gamma_{36}\ln(x/p^*) + \zeta_3 \tag{4.39}$$

for the measurement equation part

$$y_1 = \Xi + \epsilon_1 \tag{4.40}$$

$$y_2 = \Lambda_{y21}\Xi + \epsilon_2 \tag{4.41}$$

$$y_3 = w_1 \tag{4.42}$$

$$y_4 = w_2 \tag{4.43}$$

where $var(\zeta)=\Psi$, $var(\epsilon)=\Theta$.

It is very difficult to set up the MIMIC model in the same notation as the multiple indicator model. In order to make the notation as close to uniform as possible and easy to compare, the estimates presented in chapter 5 (table 13) continue using the notation of LAT/AIDS multiple indicator model when any pair of parameters have same meaning, for these parameters unique to MIMIC model the notation still follows these of (4.39)-(4.43).

The scale constraint makes Λ_{y11} equal to one. Only the first variable in η is a latent preference variable which is measured with error.

Dynamic Multiple Indicator Multiple Cause Model

The Dynamic Multiple Indicator Multiple Cause (DYMIMIC) model is an extension of the MIMIC model that permits the latent variable to follow an auto-regressive path. The possibility that the taste variable is affected by its lag has intuitive appeal since taste formation is a gradual and smooth process, which may depend on the its level of previous period. The state space form is

$$Y_t = B\ \Xi_t + X_t\Gamma + e_t \tag{3.27}$$

$$\Xi_t = \phi\ \Xi_{t-1} + F_t\delta + \mu_t \tag{3.28}$$

For the LAT/AIDS model

$$Y_t = [w_{1t}\ w_{2t}\ w_{3t}\ \text{milk}_t\ 1/\text{egg}_t]';$$

$$X_t = [\ln p_{1t}\ \ln p_{2t}\ \ln p_{3t}\ \ln(x/p^*)_t];$$

$$F_t = [\text{CHOLE}_t\ \text{WOM}_t];$$

and

$$\Xi_t = \phi\ \Xi_{t-1} + \delta_1\text{CHOLE}_t + \delta_2\text{WOM}_t + \mu_{1t} \tag{4.44}$$

$$w_{1t} = B_1\Xi_t + \Gamma_{11}\ln p_{1t} + \Gamma_{21}\ln p_{2t} + \Gamma_{31}\ln p_{3t} + \Gamma_{41}\ln(x/p^*)_t + e_{1t} \tag{4.45}$$

$$w_{2t} = B_2\Xi_t + \Gamma_{12}\ln p_{1t} + \Gamma_{22}\ln p_{2t} + \Gamma_{32}\ln p_{3t} + \Gamma_{42}\ln(x/p^*)_t + e_{2t} \tag{4.46}$$

$$w_{3t} = B_3\Xi_t + \Gamma_{13}\ln p_{1t} + \Gamma_{23}\ln p_{2t} + \Gamma_{33}\ln p_{3t} + \Gamma_{43}\ln(x/p^*)_t + e_{3t} \tag{4.47}$$

$$\text{MILK}_{1t} = B_4\Xi_t + e_{4t} \tag{4.48}$$

$$(1/\text{EGG})_{2t} = B_5\Xi_T + e_{5t} \tag{4.49}$$

where var(μ)=v, var(e)=Ψ.

The variable "MILK" and "WOM" etc. in the above specification are the same as the those of the MIMIC model.

CHAPTER 5
ESTIMATION AND RESULTS

Multiple Indicator Model

The LAT/AIDS and LAT/Rotterdam models are estimated using the models defined in chapter 4. The results of these estimations indicate that the latent preference variable has been significant in both models. The latent preference variable has a negative effect on the demand of beef, a positive effect on the demand of poultry, a positive but insignificant effect on the demand of pork. The latent AIDS and Rotterdam model yield better statistical performance than the conventional AIDS and Rotterdam model. The theoretical assumptions of utility maximization, such as symmetry, homogeneity and negativity, are satisfied in the latent models.

The data used in this study are mainly from various issues of "Food Consumption, Prices, and Expenditure"(USDA). Aggregate per capita U.S. consumption of beef, pork and poultry data, along with the average whole country nominal retail prices are used. The utilization of aggregate price and quantity data will render testing of demand properties difficult, as was discussed in the Chapter 2.

Latent AIDS Model

The LAT/AIDS model used in this research is expressed like

$$w_i = \alpha_i + \Sigma_j \tau_{ij} \ln p_j + \beta_i \ln[x/p^*] + \phi_i \Xi + \zeta_i \tag{5.1}$$

$$x = \Lambda_x \Xi + \delta \tag{5.2}$$

where the ratio of low fat milk with respect to plain whole milk, and a cholesterol index citing the number of publications linking cholesterol intake with heart problems (Brown and Schrader, 1990) serve as the indicators of latent taste variable.

The nature of the share equation system makes the LAT/AIDS model residual covariance matrix singular, so one of the equations is dropped arbitrarily for estimation. The intercepts are eliminated by subtracting means of all observable variables. In this case, the difference of the original latent variable from its mean, Ξ-Ξ, enters into the latent variable equation and measurement equations. To make the model identifiable, some constraints are imposed on the model. The latent variable has the same scale as the first indicator, low fat milk ratio. In this case, Λ_{x11} equals one. The residual covariance matrices of both latent variable and measurement equations, Θ_δ and Ψ, are diagonal.

There is no good statistic to test the goodness of fit of this structural equation model. One test statistic proposed by Bollen (1989) which uses a likelihood ratio test is plagued by its strict assumption about the observable

variable distribution and sample size. An ad hoc goodness of fit index (GFI) is used in this study to calibrate the match of S to $\hat{\Sigma}$. The exact distribution of this index is unknown, but it at least provides us with an overall model fitness measurement.

$$GFI = 1 - \frac{tr[(\hat{\Sigma}^{-1}S - I)^2]}{tr[(\hat{\Sigma}^{-1}S)^2]} \tag{5.3}$$

The GFI measures the relative amount of the variance and covariances in S that are predicted by $\hat{\Sigma}$. It reaches its maximum of one when $S = \hat{\Sigma}$. The GFI of LAT/AIDS model is 0.75, which indicates a fairly good overall fit of the model.

Table 1 reports the estimates of LAT/AIDS model without any theoretical constraints except for adding-up which is automatically satisfied. The estimates of β classify beef as luxury, pork and poultry as necessity. All but one of the τ coefficients are significantly differently from zero, having t values absolutely greater than 2. An increase of poultry price, holding other things constant, has a positive effect on the expenditure share of poultry. This effect is not significantly different from zero. The latent variable, its deviation from mean in this case, has a significant negative impact on beef consumption and positive impact on poultry consumption, while its impact on pork consumption is neutral.

Table 2 gives the latent variable (its deviation from mean) estimate from equation (5.1). This is a taste index representing adjustment of consumer taste. The t values show that the latent variable has been significant through the data range. The latent taste variable is a monotonic increasing series which has a breaking point from negative to positive in early 70's. The monotonic increasing index of consumer taste should only serve as an indicator showing the velocity of the change of taste. Whether this index is increasing or decreasing does not suggest whether the consumer tastes are "increasing" or "decreasing". We must keep in mind that the latent taste variable was made to have the same scale as one of its indicators. So the meaning of the estimated "increasing" taste variable can only be determined by comparing signs with its indicator. The taste index series is a weighted combination of the four indicators[1] which all have mean zero. The increasing taste index shows the part of increasing low fat milk ratio caused by taste change. Although the taste index changes sign from negative to positive around 1973, the locus of change clearly indicates a slow adjustment over the entire sample period. The last three columns are products of the estimated latent variable with its coefficients, $\phi(\Xi-\bar{\Xi})$. These estimates show the total effects of preference change

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[1]. The two indicators in LAT/AIDS equations (5.1) are residuals of regular AIDS share equation.

on the expenditure shares of the three meats. The remainder effect that is not explained by price and income changes in the demand models, and solely attributed to taste change. The signs of coefficients ϕ show whether taste change has positive or negative effects on expenditure shares. The relative indices of the three latent effects clearly show that the preference change over the past three decades has been in favor of poultry and disfavor of beef (Figure 3). The elasticities with respect to latent preference (Table 3) show that preference change has a positive effect on poultry consumption, and this elasticity is growing. Preference change leads to a decline in beef consumption, and the reaction becomes more elastic. This is probably because that as the knowledge about cholesterol spreads, more people are aware of the link between their food intake and health, and more people are becoming responsive to health concerns.

The expenditure and price elasticities for average data are presented in Table 4. Both the correct elasticity form presented by Green and Alston (1990) and its approximation assuming constant share expenditure are calculated. The signs of the elasticities are the same for both estimates and the numerical estimates are close. This implies that the shares do remain relatively the same throughout the sample period, and price changes have little effect on the shares of expenditures; the changes of expenditure shares depend primarily on non-price factors, such as preference changes.

The expenditure elasticities indicate strongly that beef is a luxury commodity and pork and poultry are necessity. Pork and poultry are substitute commodities. The pattern over time shows that consumers have become more and more responsive to changes in the price of pork.

The homogeneity and symmetry restrictions are tested, for the two equation latent variable model, the overall homogeneity restrictions are not rejected by the likelihood ratio test (test value is 4.17, $x^2(2)$ is 5.99 at 0.05 significant level). The combined homogeneity and symmetry restrictions are rejected (test value is 16.04, $x^2(3)$ is 7.81 at 0.05 level). Taking each of the commodities separately for the homogeneity test, beef and pork fail to reject the null hypothesis, while poultry rejects the restriction. Poultry demand increases when the prices of poultry, beef and pork increase at the same rate as the total expenditure, this "money illusion" can be attributed partially to consumer preference change. The restricted LAT/AIDS coefficients are presented in table 5.

An iterative procedure can be used to estimate the latent taste variable. The GLS estimates of taste variable from equation (3.26) can be used to calculate initial coefficients estimates for the Maximum Likelihood estimator. This iteration continues until the latent taste variable converges. The procedure converges for the above model in the second iteration, and there is very little gain in doing

the iteration and therefore is not recommended for other studies.

Latent Rotterdam Model

The Rotterdam model is similar to the first difference form of the AIDS model. The difference in the dependent variable is, instead of using Δw_i, $w_i \Delta \ln q_i$. Among the independent variables ($\Sigma w_i \Delta \ln qi$) replaces ($\Delta \ln[x/p^*]$).

$$w_i \Delta \ln q_i = \sum_j \tau_{ij} \Delta \ln p_j + \beta i \sum_k w_k \Delta \ln q_k + \phi_i \Delta \ln \Xi + e_i \qquad (5.4)$$

$$x_i = \Lambda_x \Xi + \delta_i \qquad (5.5)$$

The coefficients of three equation latent Rotterdam model are presented in table 6. The overall Goodness of Fit Index (GFI) for the LAT/Rotterdam model is 0.67. The latent preference variable is not significantly different from zero in the three latent equations. This can be attributed to the fact that after taking first difference form the variation of the data is decreased dramatically. The aggregate data used in this study are per capita consumption and retail prices, they have little variation over the years. After taking the Logarithm and first difference form, there is still much less variation left. The coefficients show the effects of the latent variable on the dependent variables. The estimated price and expenditure elasticities are presented in table 7. Pork is ranked as a luxury commodity in addition to beef. The own price elasticities are negative, and only beef is price elastic. The own price elasticity estimation is close to that of the

level data LAT/AIDS estimation. The cross price elasticities of pork with respect to poultry become negative in contrast to level data model. The estimated latent variable increments over the years are presented in table 8. The changing latent effects show a decreasing beef demand, and increasing pork and poultry demands.

The model fails to reject the overall homogeneity restriction. Separate tests indicate that if all prices and expenditure increases at the same rate, beef demand would not remain the same; the homogeneity restriction for pork and poultry applies. The test for combined homogeneity and symmetry are rejected at the one percent significance level. The parameter estimates under homogeneity and symmetry restrictions are in table 9.

The first difference data AIDS model is also estimated for comparison, the results are in table 10. The parameter estimates are not very close to the level data results, indicating a certain degree of model misspecification. The latent variable is not significant in the three latent equations, and the results of theoretic restrictions are not so evidently consistent with the data. The price and expenditure elasticities are very close to the Rotterdam results both in signs and values. Especially the own price elasticities are almost identical from both estimates. The fact that very close estimates from both first difference AIDS and Rotterdam indicates that the former as a flexible

functional form gives a good approximation for local utility maximization. The difference between estimates from level and difference AIDS form may show possible existence of serial autocorrelation in level model.

Table 1. The LAT/AIDS Coefficient Estimates (three equations)

Parameters	Coefficients	Standard Errors
Beef		
τ_{11}	0.0571	0.0124
τ_{12}	0.0430	0.0154
τ_{13}	-0.0802	0.0153
β_1	0.2187	0.0329
ϕ_1	-0.0125	0.0016
Ψ_{11}	0.0066	0.0014
Pork		
τ_{21}	-0.0355	0.0099
τ_{22}	-0.0353	0.0126
τ_{23}	0.0599	0.0124
β_2	-0.1605	0.0264
ϕ_2	0.0055	0.0012
Ψ_{22}	0.0052	0.0006
Poultry		
τ_{31}	-0.0329	0.0099
τ_{32}	-0.0081	0.0126
τ_{33}	0.0137	0.0124
β_3	-0.0631	0.0264
ϕ_3	0.0096	0.0012
Ψ_{33}	0.0024	0.0006
Indicator Equation		
Φ	2.7196	0.3280
Θ_1	0.6116	0.0988
Θ_2	0.2413	0.0392
Θ_{12}	0.1433	0.0467
λ_{x2}	0.3642	0.0035

Table 2. Latent Taste Index and The Latent Effects 1950-1987

Year	Latent (df)	t-value	Beef	Pork	Poultry
1950	-2.21674	-3.32734	0.02780	-0.01227	-0.02125
1951	-2.20548	-3.31044	0.02766	-0.01221	-0.02114
1952	-2.23767	-3.35876	0.02806	-0.01239	-0.02145
1953	-2.26602	-3.40131	0.02842	-0.01255	-0.02172
1954	-2.35647	-3.53707	0.02955	-0.01305	-0.02259
1955	-2.36819	-3.55467	0.02970	-0.01311	-0.02270
1956	-2.38446	-3.57909	0.02990	-0.01320	-0.02285
1957	-2.40489	-3.60975	0.03016	-0.01331	-0.02305
1958	-2.37804	-3.56945	0.02982	-0.01317	-0.02279
1959	-2.35694	-3.53778	0.02956	-0.01305	-0.02259
1960	-2.35666	-3.53736	0.02955	-0.01305	-0.02259
1961	-2.29845	-3.44999	0.02882	-0.01273	-0.02203
1962	-2.26666	-3.40226	0.02843	-0.01255	-0.02172
1963	-2.23729	-3.35819	0.02806	-0.01239	-0.02144
1964	-2.14364	-3.21761	0.02688	-0.01187	-0.02055
1965	-2.07982	-3.12183	0.02608	-0.01152	-0.01993
1966	-2.01281	-3.02124	0.02524	-0.01114	-0.01929
1967	-1.79195	-2.68972	0.02247	-0.00992	-0.01717
1968	-1.49630	-2.24596	0.01876	-0.00828	-0.01434
1969	-1.19689	-1.79654	0.01501	-0.00663	-0.01147
1970	-0.95950	-1.44022	0.01203	-0.00531	-0.00920
1971	-0.72038	-1.08129	0.00903	-0.00399	-0.00690
1972	-0.40989	-0.61525	0.00514	-0.00227	-0.00393
1973	0.01742	0.02614	-0.00022	0.00010	0.00017
1974	0.33875	0.50847	-0.00425	0.00188	0.00325
1975	0.76292	1.14515	-0.00957	0.00422	0.00731
1976	1.18119	1.77297	-0.01481	0.00654	0.01132
1977	1.65297	2.48112	-0.02073	0.00915	0.01584
1978	1.98365	2.97748	-0.02488	0.01098	0.01901
1979	2.38551	3.58066	-0.02992	0.01321	0.02286
1980	2.85627	4.28728	-0.03582	0.01581	0.02738
1981	3.29228	4.94174	-0.04129	0.01823	0.03155
1982	3.60287	5.40793	-0.04518	0.01995	0.03453
1983	4.02660	6.04395	-0.05050	0.02229	0.03859
1984	4.55500	6.83708	-0.05712	0.02522	0.04366
1985	5.26382	7.90103	-0.06601	0.02914	0.05045
1986	6.21796	9.33320	-0.07798	0.03443	0.05960
1987	7.00791	10.51892	-0.08789	0.03880	0.06717

Table 3. Latent Elasticity

Years	Beef	Pork	Poultry
1950	0.05289	-0.03885	-0.13407
1951	0.05262	-0.03865	-0.13338
1952	0.05339	-0.03922	-0.13533
1953	0.05407	-0.03971	-0.13705
1954	0.05622	-0.04130	-0.14252
1955	0.05650	-0.04150	-0.14323
1956	0.05689	-0.04179	-0.14421
1957	0.05738	-0.04215	-0.14544
1958	0.05674	-0.04168	-0.14382
1959	0.05623	-0.04131	-0.14254
1960	0.05623	-0.04130	-0.14253
1961	0.05484	-0.04028	-0.13901
1962	0.05408	-0.03972	-0.13708
1963	0.05338	-0.03921	-0.13531
1964	0.05115	-0.03757	-0.12964
1965	0.04962	-0.03645	-0.12579
1966	0.04802	-0.03528	-0.12173
1967	0.04275	-0.03141	-0.10837
1968	0.03570	-0.02622	-0.09049
1969	0.02856	-0.02098	-0.07239
1970	0.02289	-0.01682	-0.05803
1971	0.01719	-0.01263	-0.04357
1972	0.00978	-0.00718	-0.02479
1973	-0.00042	0.00031	0.00105
1974	-0.00808	0.00594	0.02049
1975	-0.01820	0.01337	0.04614
1976	-0.02818	0.02070	0.07144
1977	-0.03944	0.02897	0.09997
1978	-0.04733	0.03477	0.11997
1979	-0.05692	0.04181	0.14427
1980	-0.06815	0.05006	0.17274
1981	-0.07855	0.05770	0.19911
1982	-0.08596	0.06314	0.21790
1983	-0.09607	0.07057	0.24352
1984	-0.10868	0.07983	0.27548
1985	-0.12559	0.09225	0.31835
1986	-0.14836	0.10897	0.37605
1987	-0.16720	0.12282	0.42383

Table 4. LAT/AIDS Price and Expenditure Elasticities

Price Elasticity (Ray & Alston)

	Beef	Pork	Poultry
Beef	-1.0967	-0.0462	-0.1983
Pork	0.1385	-0.9554	0.2455
Poultry	-0.0114	0.0711	-0.8700

Price Elasticity (constant share assumed)

	Beef	Pork	Poultry
Beef	-1.1101	-0.0497	-0.2185
Pork	0.1548	-0.9511	0.2702
Poultry	0.0014	0.0744	-0.8506

Expenditure Elasticity

Beef	1.4161
Pork	0.4919
Poultry	0.6019

Table 5. LAT/AIDS Model With Homogeneity Restriction

Parameters	Coefficients	Standard Errors
Beef		
τ_{11}	0.0472	0.0122
τ_{12}	0.0436	0.0161
β_1	0.2182	0.0333
ϕ_1	-0.0954	0.0074
Ψ_1	0.0078	0.0009
Pork		
τ_{21}	-0.0281	0.0111
τ_{22}	-0.0345	0.0146
β_2	-0.1556	0.0302
ϕ_2	0.0343	0.0067
Ψ_2	0.0071	0.0008
Indicator Equations		
Φ	0.2787	0.0320
Θ_1	0.0300	0.0117
Θ_2	0.0587	0.0067
λ_{x2}	3.6517	0.0341

LAT/AIDS Model With Homogeneity and Symmetry Restriction

Parameters	Coefficients	Standard Errors
Beef		
τ_{11}	0.0636	0.0119
τ_{12}	0.0025	0.0107
β_1	0.2744	0.0321
ϕ_1	-0.0941	0.0081
Ψ_1	0.0085	0.0011
Pork		
τ_{22}	-0.0538	0.0143
β_2	-0.1582	0.0326
ϕ_2	0.0195	0.0156
Ψ_2	0.0076	0.0010
Indicator Equations		
Φ	0.2787	0.0320
Θ_1	0.0055	0.0007
Θ_2	0.0554	0.0113
λ_{x2}	3.6530	0.0345

Table 6. LAT/Rotterdam Model Estimate

Parameters	Coefficients	Standard Errors
Beef		
τ_{11}	-0.2359	0.0204
τ_{12}	0.1505	0.0194
τ_{13}	0.0493	0.0222
β_1	0.6185	0.0646
ϕ_1	-0.0851	0.0557
Ψ_{11}	0.0079	0.0009
Pork		
τ_{21}	0.1926	0.0193
τ_{22}	-0.1798	0.0184
τ_{23}	0.0257	0.0210
β_2	0.3584	0.0611
ϕ_2	0.0606	0.0526
Ψ_{22}	0.0075	0.0009
Poultry		
τ_{31}	0.0433	0.0085
τ_{32}	0.0305	0.0082
τ_{33}	-0.0765	0.0094
β_3	0.0268	0.0271
ϕ_3	0.0350	0.0221
Ψ_{33}	0.0033	0.0004
Indicator Equations		
Φ	0.0240	0.0031
Θ_1	0.0092	0.0011
Θ_2	0.0321	0.0037
λ_{x2}	3.7450	0.2325

Table 7. LAT/Rotterdam Price & Expenditure Elasticity

	Expenditure Elasticity
Beef	1.1767
Pork	1.1345
Poultry	0.1691

Price Elasticity

	Beef	Pork	Poultry
Beef	-1.0673	-0.0855	-0.0926
Pork	0.0135	-0.9274	-0.0984
Poultry	0.1846	0.1391	-0.5098

Table 8. LAT/Rotterdam Latent Variable

Years	Latent Var.	t-value	Latent Curve Beef	Pork	Poultry
1950	-0.00030	-0.16309	0.00003	-0.00002	-0.00001
1951	-0.00084	-0.46014	0.00007	-0.00005	-0.00003
1952	-0.00062	-0.33915	0.00005	-0.00004	-0.00002
1953	-0.00251	-1.37129	0.00021	-0.00015	-0.00009
1954	0.00006	0.03511	-0.00001	0.00000	0.00000
1955	-0.00067	-0.36653	0.00006	-0.00004	-0.00002
1956	-0.00090	-0.49300	0.00008	-0.00005	-0.00003
1957	0.00035	0.19270	-0.00003	0.00002	0.00001
1958	0.00068	0.37328	-0.00006	0.00004	0.00002
1959	0.00020	0.10795	-0.00002	0.00001	0.00001
1960	0.00131	0.71906	-0.00011	0.00008	0.00005
1961	0.00081	0.44360	-0.00007	0.00005	0.00003
1962	0.00070	0.38538	-0.00006	0.00004	0.00002
1963	0.00234	1.27969	-0.00020	0.00014	0.00008
1964	0.00150	0.82020	-0.00013	0.00009	0.00005
1965	0.00378	2.06841	-0.00032	0.00023	0.00013
1966	0.02960	16.20079	-0.00252	0.00179	0.00104
1967	0.03978	21.77008	-0.00339	0.00241	0.00139
1968	0.03136	17.16421	-0.00267	0.00190	0.00110
1969	0.02878	15.75259	-0.00245	0.00174	0.00101
1970	0.02629	14.38736	-0.00224	0.00159	0.00092
1971	0.02942	16.10098	-0.00250	0.00178	0.00103
1972	0.03892	21.29788	-0.00331	0.00236	0.00136
1973	0.03918	21.44239	-0.00334	0.00238	0.00137
1974	0.04587	25.10261	-0.00390	0.00278	0.00161
1975	0.04007	21.92863	-0.00341	0.00243	0.00140
1976	0.03948	21.60608	-0.00336	0.00239	0.00138
1977	0.02899	15.86276	-0.00247	0.00176	0.00102
1978	0.03580	19.59277	-0.00305	0.00217	0.00125
1979	0.03301	18.06276	-0.00281	0.00200	0.00116
1980	0.03728	20.40376	-0.00317	0.00226	0.00131
1981	0.03760	20.57712	-0.00320	0.00228	0.00132
1982	0.04585	25.09254	-0.00390	0.00278	0.00161
1983	0.05558	30.41566	-0.00473	0.00337	0.00195
1984	0.06980	38.19692	-0.00594	0.00423	0.00245
1985	0.08406	46.00508	-0.00716	0.00510	0.00295
1986	0.07771	42.53025	-0.00662	0.00471	0.00272

Table 9. LAT/Rotterdam Model With Homogeneity

Parameters	Coefficients	Standard Errors
Beef		
τ_{11}	-0.2059	0.0210
τ_{12}	0.1670	0.0212
β_1	0.7172	0.0613
ϕ_1	-0.1369	0.0706
Ψ_1	0.0102	0.0012
Pork		
τ_{21}	0.1858	0.0146
τ_{22}	-0.1882	0.0148
β_2	0.3495	0.0426
ϕ_2	0.0594	0.0488
Ψ_2	0.0071	0.0008
Indicator Equations		
Φ	0.0240	0.0031
Θ_1	0.0092	0.0011
Θ_2	0.0041	0.0009
λ_{x2}	3.7450	0.2325

Rotterdam Model With Homogeneity and Symmetry Restricted

Parameters	Coefficients	Standard Errors
Beef		
τ_{11}	-0.2083	0.0209
τ_{12}	0.1777	0.0171
β_1	0.7224	0.0606
ϕ_1	-0.1352	0.0702
Ψ_1	0.0101	0.0012
Pork		
τ_{22}	-0.1130	0.0222
β_2	0.6038	0.0717
ϕ_2	-0.0247	0.0727
Ψ_2	0.0106	0.0012
Indicator Equations		
Φ	0.0240	0.0032
Θ_1	0.0094	0.0011
Θ_2	0.0041	0.0019
λ_{x2}	3.7450	0.2368

Table 10. LAT/AIDS (First Difference Form)

Parameters	Coefficients	Standard Errors
Beef		
τ_{11}	-0.0035	0.0225
τ_{12}	-0.0258	0.0216
τ_{13}	-0.0291	0.0237
β_1	0.0285	0.0775
ϕ_1	-0.1358	0.0904
Ψ_{11}	0.0076	0.0014
Pork		
τ_{21}	0.0375	0.0206
τ_{22}	0.0449	0.0196
τ_{23}	-0.0342	0.0215
β_2	0.0880	0.0705
ϕ_2	0.1114	0.0747
Ψ_{22}	0.0034	0.0004
Poultry		
τ_{31}	-0.0336	0.0094
τ_{32}	-0.0156	0.0091
τ_{33}	0.0594	0.0099
β_3	-0.1062	0.0328
ϕ_3	0.0393	0.0503
Ψ_{33}	0.0016	0.0036
Indicator Equations		
Φ	0.0638	0.0434
Θ_1	0.2490	0.0288
Θ_2	0.0869	0.0100
Θ_{12}	0.0201	0.0048
λ_{x2}	0.3645	0.0891

Table 11. LAT/AIDS (First Difference Form) Elasticities

Price Elasticities

	Beef	Pork	Poultry
Beef	-1.0339	-0.0654	-0.0614
Pork	-0.0214	-0.9418	-0.1394
Poultry	0.1247	0.1032	-0.5504

Price Elasticity (approximation)

	Beef	Pork	Poultry
Beef	-1.0352	-0.0662	-0.0639
Pork	-0.0277	-0.9459	-0.1524
Poultry	0.1399	0.1130	-0.5191

Expenditure Elasticity

Beef	1.0543
Pork	1.2786
Poultry	0.3299

Table 12. LAT/AIDS (First Difference Form) Latent Elasticity

Years	Beef	Pork	Poultry
1950	-0.01414	0.01930	0.01358
1951	0.02522	-0.03442	-0.02422
1952	0.00639	-0.00871	-0.00613
1953	0.01592	-0.02173	-0.01529
1954	0.00312	-0.00426	-0.00299
1955	0.01158	-0.01581	-0.01112
1956	0.00898	-0.01225	-0.00862
1957	0.00505	-0.00690	-0.00485
1958	-0.00066	0.00090	0.00064
1959	0.00280	-0.00382	-0.00269
1960	-0.00371	0.00507	0.00356
1961	-0.00096	0.00131	0.00092
1962	0.00236	-0.00322	-0.00226
1963	-0.00510	0.00696	0.00490
1964	-0.00099	0.00135	0.00095
1965	-0.00476	0.00650	0.00457
1966	-0.02638	0.03600	0.02533
1967	-0.02378	0.03246	0.02284
1968	-0.02560	0.03494	0.02458
1969	-0.02836	0.03870	0.02723
1970	-0.02022	0.02759	0.01941
1971	-0.01951	0.02662	0.01873
1972	-0.05276	0.07201	0.05067
1973	-0.02823	0.03853	0.02711
1974	-0.03618	0.04938	0.03474
1975	-0.05289	0.07218	0.05079
1976	-0.05960	0.08134	0.05723
1977	-0.02676	0.03653	0.02570
1978	-0.04459	0.06085	0.04282
1979	-0.05443	0.07428	0.05227
1980	-0.05184	0.07075	0.04978
1981	-0.03320	0.04531	0.03188
1982	-0.05685	0.07759	0.05460
1983	-0.06013	0.08207	0.05775
1984	-0.09278	0.12663	0.08910
1985	-0.09887	0.13495	0.09495
1986	-0.10279	0.14029	0.09871
	Average Latent Elasticity		
	-0.00413	0.00461	0.00609

MIMIC Model

The GFI of LAT/AIDS model is 0.65, which indicates a fairly good overall fit for the model. The coefficients of determination (R^2_i) for the three LA\AIDS model are very high, indicating a good fit for individual equations (Table 13). The coefficient of determination for the y measurement model provides a summary of the joint fit of the y variables, defined as $1-|\Theta_\delta|/|\Sigma_{yy}|$.

The equations for MIMIC model in chapter 4 can be expressed in a compact form as:

$$w_i = \alpha_i + \sum_j \tau_{ij} \ln p_j + \beta_i \ln[x/p^*] + \phi_i \Xi + e_i \qquad (5.6)$$

$$x_i = \Lambda_x \, \Xi + e_i \qquad (5.7)$$

$$\Xi_t = \sum_k \Gamma_k w_k + \zeta_i \qquad (5.8)$$

Coefficient estimates of LAT/AIDS model are given in table 13. The parameters of LAT/AIDS model in the latent variable model (4.38)-(4.39) are replaced by the notation used in equation (5.6), the rest of the notation follows equation (4.37) and (4.40)-(4.43). The estimated coefficients ϕ_i indicate that the latent preference variable has been significant in beef and poultry demand equations. The latent preference variable has a negative effect on the demand for beef, a positive effect on the demand for poultry, a positive but insignificant effect on the demand for pork. The latent AIDS model gives better statistical

performance than the conventional AIDS model. The estimates of β_i classifies beef as a luxury, and both pork and poultry as necessities. That means when income increases, the expenditure shares of pork and poultry would decrease while that of beef increases. All but two τ_{ij} coefficients are significantly differently from zero, having t values absolutely greater than 2. Λ_{y21} is 1.13×10^{-3} which suggests that decreasing egg consumption (increasing its inverse) has a positive effect on the latent preference variable. Γ_{11} and Γ_{12} show the effects of the two cause variables on the latent preference variable. Both of the coefficients are positive and significant, indicating a strong relationship exists between the latent taste variable and two cause variables.

The expenditure and price elasticities for average data are presented in Table 14. Both the correct price elasticities using the linear AIDS model presented by Green and Alston (1990), and its approximation assuming constant share expenditure, are calculated. The signs of the elasticities are the same for both estimates and the numerical values are very close, indicating that the approximation is useful. On the other hand it implies that price changes have little effect on shares of expenditure and that the changes of expenditure shares depends primarily on non-price factors, such as preference changes. The expenditure elasticities indicate strongly that beef is a

luxury commodity while pork and poultry are necessities. If pork and poultry prices increase, the quantity of beef consumption would decrease. On the other hand, an increase of beef price would elicit substitutive increases in consumption of pork and poultry. Pork and poultry are substitute commodities. The pattern over time (estimated price and expenditure elasticities 1965-1985) shows that consumers become more responsive to changes in the price of pork, but less responsive to price changes in beef and poultry.

The latent variable (with mean zero) is estimated using the general estimator (3.25)-(3.26). In the MIMIC model, the cause equation also should be taken into consideration. The equation (5.7) can be written as $x = \hat{\Lambda}_x \Xi + \hat{\epsilon}$, where $\hat{\Lambda}_x = [1\ \Lambda_{x21}]'$, $\epsilon \sim N(0, \Theta)$. The equation (5.8) can be rewritten as $\Xi = w\Gamma + \zeta_1$, where w=[CHOLE WOM]', $\zeta_1 \sim N(0, \Psi)$. Then

$$\hat{\Xi}_{1t} = w_t\hat{\Gamma} + \hat{\Psi}\hat{\Lambda}_x'(\hat{\Lambda}_x\hat{\Psi}\hat{\Lambda}_x'+\hat{\Theta})^{-1}(x_t - \hat{\Lambda}_x w_t \hat{\Gamma}) \qquad (5.10)$$

$$\mathrm{Var}(\hat{\Xi}_{1t}) = \hat{\Psi} - \hat{\Psi}\hat{\Lambda}_x'(\hat{\Lambda}_x\hat{\Psi}\hat{\Lambda}_x' + \hat{\Theta})^{-1}\hat{\Lambda}_x\hat{\Psi} \qquad (5.11)$$

The t values show that the latent variable has been significant throughout the data range. The latent variable (deviation from mean) is a increasing series which has a breaking point from negative to positive in mid 70's. Again there is no indication that there is an abrupt change of tastes. The locus of preference change clearly indicates slow adjustment over the entire sample period. The products

of the estimated latent variable with its coefficients, $\phi(\Xi-\bar{\Xi})$, trace out the total latent effects of preference change on the expenditure shares of all three meats. The relative indices of the three latent effects clearly show that preference changes over the past three decades have been in favor of poultry and against beef (Figure 3). The elasticities with respect to latent preferences (Table 15) show that preference change has a positive and increasing effect on poultry consumption. Preference change has led to a decline in beef consumption. Moreover, the elasticities in table 14 suggest that this decline has become more rapid in the latest few years. The inclusion of the convenience demand variable slightly increased consumer taste change speed (Table 16).

Good indicator and cause variables are important to structural equation models. But latent structural model rely much less heavily on these variables than regression analysis using a taste instrument variable as an exogenous variable. The estimated taste variable is an optimal combination of the indicator and cause variables given the data and structural specifications. Furthermore, the fact that the parameters $\Theta_{\epsilon 11}$, $\Theta_{\epsilon 22}$ and Ψ_{11} are significantly different than zero confirms that the indicator and cause variables are measured with error and should not be used individually or together without accounting for this source of measurement error.

Estimates of latent taste index is used to calculate the efects of taste on meat demand. It is found that taste change had decreased per capita beef consumption by 24 percent, had increased pork and poultry consumption by 7 and 65 percent, respectively over the entire data range 1950-1987 (Table 17). Most of the preference change took effects after 1970's. From 1970-1987, preference change has decreased beef demand by 17 percent, increased pork and poultry demand by 5 and 47 percents. That means about 90 percent of preference change happened after 1970. During the 80's, preference change continue to occur, and at an accelerating speed. If the trend in preferences continues at the present rate, ceteris paribus, the per capita consumption of beef will continue declining, falling by 19 percent over the next ten years; the consumption of pork will increase by 6 percent, while the consumption of poultry will increase by 53 percent over the next 10 years. This prediction is possibly biased upward since we used taste change trend of the past 38 years to make the predictions. It is unlikely that the industry will continue ignoring changing market conditions in the next decade and make mistakes as pointed out by Purcell (1989), especially after so much exposure of the issues in the recent years.

The estimated value of the latent preference variable can be used to show the effects of the latent preference variable on price and expenditure elasticities by assuming

price and expenditure coefficients vary with the preference variable. The AIDS model is re-estimated by including interaction terms ($\ln p_i\hat{\Xi}$) and ($\ln(x/p^*)\hat{\Xi}$ in each equation. This comes by assuming the parameters in LAT/AIDS model are a function of the latent preference variable:

$$w_i = \alpha_i + \sum_j \tau_{ij}\ln p_j + \beta_i \ln[x/p^*] + \phi_i\hat{\Xi} + \zeta_i \qquad (4.9)$$

$$\tau_{ii}=\tau_{i0}+\tau_{i1}\hat{\Xi} \qquad (5.12)$$

$$\beta_i=\beta_{i0} +\beta_{i1}\hat{\Xi} \qquad (5.13)$$

Notice the change in the poultry and beef equations (Table 18). The positive interactions of poultry price and the taste variable, and the negative interaction of expenditure with the taste variable indicate a damping effect on the absolute price and expenditure elasticities of poultry. Consumers are less responsive to price and expenditure changes when taste change is jointly considered in their demand model. Increasing the price of poultry decreases poultry consumption less than would be the case without the taste change. Increasing the price of beef decreases beef consumption more than would be the case without the taste change.

Table 13. MIMIC Model Results

Parameter[2]	Coefficient	Standart Error
Beef		
τ_{11}	0.05384	0.01264
τ_{12}	0.04860	0.01584
τ_{13}	-0.07635	0.01602
β_1	0.23463	0.03411
ϕ_1	-0.01306	0.00198
Ψ_{22}	0.00748	0.00088
Pork		
τ_{21}	-0.02524	0.01157
τ_{22}	-0.03400	0.01458
τ_{23}	0.06832	0.01469
β_2	-0.15181	0.03091
ϕ_2	0.00231	0.00184
Ψ_{33}	0.00701	0.00081
Poultry		
τ_{31}	-0.02989	0.00680
τ_{32}	-0.01421	0.00853
τ_{33}	0.00922	0.00858
β_3	-0.08056	0.01789
ϕ_3	0.01073	0.00102
Ψ_{44}	0.00412	0.00048
Indicator Equation		
Λ_{y21}	0.00113	0.00009
$\Theta_{\epsilon 11}$	0.07508	0.00954
$\Theta_{\epsilon 22}$	0.00143	0.00018
$\Theta_{\epsilon 12}$	-0.00043	0.00003
Cause Equation		
Γ_{11}	2.55943	0.06753
Γ_{12}	1.94706	0.72508
Ψ_{11}	0.12685	0.05626
R^2_1	0.985	
R^2_2	0.986	
R^2_3	0.954	
GFI	0.65	

[2]. The first 15 parameters uses the notation of (5.6), others following (4.37)-(4.43).

Table 14. Price and Expenditure Elasticities

Price Elasticities

	Beef	Pork	Poultry
Beef	-1.12057	-0.04377	-0.20104
Pork	0.16017	-0.96094	0.27631
Poultry	0.06532	0.06547	-0.87830

Price Elasticity (approximation)

	Beef	Pork	Poultry
Beef	-1.13221	-0.04855	-0.21600
Pork	0.17270	-0.95580	0.29242
Poultry	0.07857	0.07091	-0.86127

Expenditure Elasticity

Beef	1.44639
Pork	0.51944
Poultry	0.49166

Table 15. Latent Elasticities

	Beef	Pork	Poultry
1950	0.0948	-0.0214	-0.2219
1951	0.0891	-0.0183	-0.1942
1952	0.0849	-0.0195	-0.1964
1953	0.0814	-0.0189	-0.1919
1954	0.0846	-0.0202	-0.2099
1955	0.0850	-0.0210	-0.2155
1956	0.0784	-0.0207	-0.2043
1957	0.0747	-0.0198	-0.1968
1958	0.0669	-0.0180	-0.1780
1959	0.0705	-0.0193	-0.2004
1960	0.0589	-0.0168	-0.1636
1961	0.0519	-0.0150	-0.1444
1962	0.0499	-0.0144	-0.1402
1963	0.0413	-0.0123	-0.1173
1964	0.0366	-0.0113	-0.1042
1965	0.0299	-0.0093	-0.0835
1966	0.0203	-0.0061	-0.0563
1967	0.0283	-0.0086	-0.0820
1968	0.0288	-0.0092	-0.0866
1969	0.0167	-0.0054	-0.0505
1970	0.0140	-0.0044	-0.0435
1971	0.0167	-0.0055	-0.0535
1972	0.0119	-0.0041	-0.0400
1973	-0.0241	0.0078	0.0678
1974	-0.0171	0.0056	0.0546
1975	-0.0276	0.0095	0.0851
1976	-0.0383	0.0127	0.1196
1977	-0.0485	0.0160	0.1434
1978	-0.0515	0.0172	0.1517
1979	-0.0556	0.0182	0.1628
1980	-0.0655	0.0214	0.1881
1981	-0.0815	0.0261	0.2233
1982	-0.0839	0.0267	0.2315
1983	-0.0947	0.0289	0.2536
1984	-0.1185	0.0374	0.2830
1985	-0.1342	0.0395	0.3091
1986	-0.1471	0.0466	0.3294
1987	-0.1626	0.0473	0.3490

Table 16. Latent Taste Index and The Latent Effects 1950-1987

Year	Latent	Beef	Pork	Poultry
1950	-3.4014	0.0444	-0.0079	-0.0365
1951	-3.0493	0.0398	-0.0070	-0.0327
1952	-3.0574	0.0399	-0.0071	-0.0328
1953	-2.9549	0.0386	-0.0068	-0.0317
1954	-3.1261	0.0408	-0.0072	-0.0336
1955	-3.1914	0.0417	-0.0074	-0.0343
1956	-3.0243	0.0395	-0.0070	-0.0325
1957	-2.8886	0.0377	-0.0067	-0.0310
1958	-2.6045	0.0340	-0.0060	-0.0280
1959	-2.7889	0.0364	-0.0064	-0.0299
1960	-2.3541	0.0307	-0.0054	-0.0253
1961	-2.0823	0.0272	-0.0048	-0.0224
1962	-2.0053	0.0262	-0.0046	-0.0215
1963	-1.6819	0.0220	-0.0039	-0.0181
1964	-1.5044	0.0196	-0.0035	-0.0161
1965	-1.2275	0.0160	-0.0028	-0.0132
1966	-0.8273	0.0108	-0.0019	-0.0089
1967	-1.1601	0.0152	-0.0027	-0.0125
1968	-1.2064	0.0158	-0.0028	-0.0130
1969	-0.7057	0.0092	-0.0016	-0.0076
1970	-0.5884	0.0077	-0.0014	-0.0063
1971	-0.7144	0.0093	-0.0016	-0.0077
1972	-0.5192	0.0068	-0.0012	-0.0056
1973	1.0049	-0.0131	0.0023	0.0108
1974	0.7289	-0.0095	0.0017	0.0078
1975	1.1880	-0.0155	0.0027	0.0128
1976	1.6329	-0.0213	0.0038	0.0175
1977	2.0470	-0.0267	0.0047	0.0220
1978	2.1805	-0.0285	0.0050	0.0234
1979	2.3396	-0.0306	0.0054	0.0251
1980	2.7447	-0.0358	0.0063	0.0295
1981	3.3708	-0.0440	0.0078	0.0362
1982	3.4639	-0.0452	0.0080	0.0372
1983	3.8431	-0.0502	0.0089	0.0413
1984	4.7639	-0.0622	0.0110	0.0511
1985	5.2476	-0.0685	0.0121	0.0563
1986	5.8517	-0.0764	0.0135	0.0628
1987	6.2562	-0.0817	0.0144	0.0672

Table 17. Meat Demands Changes Caused By Preference Changes (percentages)

	Beef	Pork	Poultry
1950-1987	-0.2400	0.0706	0.6542
1970-1987	-0.1730	0.0509	0.4716
1980-1987	-0.0973	0.0286	0.2653
Predictions (By 2000)	-0.1958	0.0576	0.5338

Table 18. MIMIC Model Joint Effect Coefficients Estimates:

	Beef		Pork		Poultry	
	coef.	sdt	coef.	sdt.	coef.	sdt.
lnp1	0.0246	0.0168	-0.0196	0.0119	-0.0171	0.0088
lnp_2	0.0335	0.0227	-0.0315	0.0159	-0.0095	0.0115
lnp_3	-0.1095	0.0223	0.0718	0.0160	0.0745	0.0132
lnx	0.1801	0.0516	-0.1331	0.0367	-0.0770	0.0261
Ξlnp_i	-0.0048	0.0034	-0.0006	0.0029	0.0174	0.0029
Ξlnx	0.0107	0.0211	0.0072	0.0176	-0.0472	0.0108

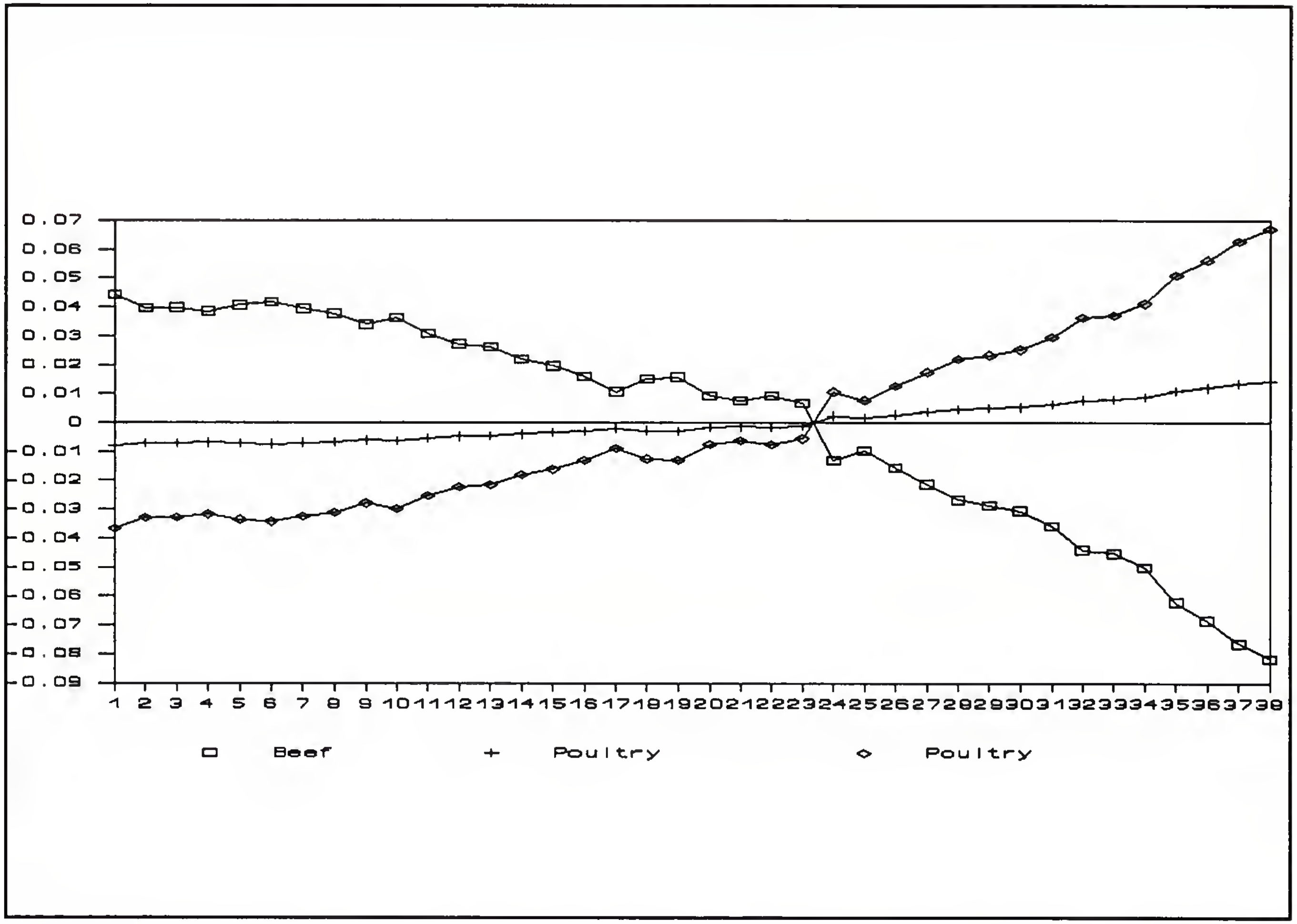

Figure 3. Effects of Latent Variable (Deviation From Mean) Change on Meat Demand (Horizontal Axis Is Years 1950-1987).

DYMIMIC Model

The DYMIMIC model specification in a compact form is

$$w_i = \sum_j \tau_{ij} \ln p_j + \beta_i \ln[x/p^*] + \phi_i \Xi y_t + e_i \qquad (5.14)$$

$$x_i = \Lambda_x \Xi_t + \delta_i \qquad (5.15)$$

$$\Xi_t = \phi \Xi_{t-1} + \sum_k \Gamma_k w_k + \zeta_i \qquad (5.16)$$

where var(e)=Ψ, var(δ)=h, var(ζ)=v.

The iteration between Kalman filter and smoother estimates were repeated three times before convergence.

The filtering likelihood function (3.37) is very difficult to converge in this particular case, due largely to the problem of little data variation. To improve the convergence performance of this problem, the base indicator, the low fat milk ratio is trended using the technique described in Harvey (1985). The trend series of the low fat milk ratio is used instead of the raw data to minimize random fluctuation. The base indicator only serves as a trend indicator for the latent variable, so the using of trended indicator would enhance rather than distort the interpretation of the model.

The raw time series indicator variable d_t (law fat milk ratio, "MILK") is a sum of its trend s_t and stochastic error term:

$$d_t = s_t + e_t \qquad (5.17)$$

The trend follows a random walk with drift and that drift parameter, b_t, itself follows a random walk:

$$s_t = s_{t-1} + b_{t-1} + v_t \tag{5.18}$$

$$b_t = b_{t-1} + u_t \tag{5.19}$$

The above trend and drift parameters can be estimated by Kalman filtering and smothering (Harvey, 1985). Assume that e_t, v_t and u_t are mutually independent white noise, with standard deviation σ, σ_v, and σ_u, a likelihood ratio test can be used to test either of them is zero. If σ is zero, trend coincides with raw series. If σ_v is zero, the growth rate of trend is random but the trend component has no discrete jumps. If σ_u is identically zero then the level of trend is subject to random shocks but the growth rate remains constant. If $\sigma_u = \sigma_v$, the simple linear trend results.

The estimated trend and drift parameters for the low fat milk ratios are shown in table 19. σ_v is tested to be zero. The trend s_t is then used in place of raw d_t.

The results of Dynamic Multiple Indicator and Multiple Cause (DYMIMIC) model is very close with that of MIMIC model. The estimates are presented in table 20. The notation follows that of the MIMIC model. The parameter of the lagged latent taste variable has the value of 0.0036, with t-value grater than 2.5, it is significantly different from zero at 3 percent significant level. This validates the dynamic specification of latent variable in the model. The fact that the coefficient of the latent lag variable has an absolute value less than unitary also make the dynamic system stationary. The effect of past latent taste on its present value decreases

as the time period increases.

The price and expenditure elasticities are presented in table 21. They are also almost identical to the results of MIMIC model and the interpretations that were given in last section. The identical expenditure and price elasticities estimated from static and dynamic model show that the price and income effects on demand changes are not significantly altered by dynamic latent taste change set-up. The coefficients estimates in the AIDS model parts of both MIMIC and DYMIMIC models are very close. The latent variable elasticities show that beef demand is declining at an increasing rate with respect to taste change, this reconfirms earlier findings that consumers are more responsive to health concerns. The latent taste index, which converges from iterations of Kalman smoother and regression, is given in Figure 4. The findings clearly show that taste is changing at a increasing speed within the data range. The speed of taste adjustment in this model is greater than that estimated by the multiple indicator model, one explanation is that the inclusion of the convenience demand variable into the cause variables makes consumers' taste changes more elastic; another explanation is the dynamic specification of taste change. The estimated effect of taste change on beef demand is very similar with the results shown in MIMIC model (table 5.22-25). But a higher percentage of poultry consumption increase is attributed to taste change in DYMIMIC than MIMIC.

Table 19. Low Fat Milk Ratio And Trend

Year	d_i	s_i	b_i
1950	1.1313	1.1313	-0.0293
1951	1.0891	1.0899	-0.0414
1952	1.0719	1.0706	-0.0200
1953	1.0396	1.0374	-0.0328
1954	0.9243	0.9306	-0.1044
1955	0.9314	0.9271	-0.0068
1956	0.9026	0.9029	-0.0236
1957	0.8684	0.8707	-0.0319
1958	0.8960	0.8944	0.0218
1959	0.9281	0.9273	0.0326
1960	0.9476	0.9493	0.0223
1961	1.0109	1.0091	0.0586
1962	1.0545	1.0549	0.0462
1963	1.0942	1.0969	0.0422
1964	1.2133	1.2098	0.1106
1965	1.2969	1.2963	0.0872
1966	1.3373	1.3435	0.0485
1967	1.5240	1.5228	0.1750
1968	1.7967	1.7940	0.2681
1969	2.0859	2.0822	0.2875
1970	2.2821	2.2866	0.2071
1971	2.5361	2.5375	0.2495
1972	2.8723	2.8714	0.3311
1973	3.2676	3.2630	0.3896
1974	3.5814	3.5872	0.3263
1975	4.0144	4.0104	0.4200
1976	4.4141	4.4177	0.4077
1977	4.9195	4.9116	0.4911
1978	5.2628	5.2689	0.3617
1979	5.6620	5.6656	0.3955
1980	6.2041	6.1966	0.5266
1981	6.6547	6.6516	0.4573
1982	6.9426	6.9511	0.3046
1983	7.3318	7.3333	0.3797
1984	7.8278	7.8309	0.4938
1985	8.5249	8.5293	0.6917
1986	9.5667	9.5474	1.0075
1987	10.3367	10.3443	0.8038

Table 20. DYMIMIC Parameter Estimates

Parameters	Coefficients	Standard Error
Beef		
τ_{11}	0.0548	0.0186
τ_{12}	0.0464	0.0233
τ_{13}	-0.0756	0.0234
β_1	0.2304	0.0490
ϕ_1	-0.0128	0.0028
Ψ_{11}	0.0112	0.0020
Pork		
τ_{21}	-0.0254	0.0176
τ_{22}	-0.0336	0.0220
τ_{23}	0.0682	0.0221
β_2	-0.1510	0.0464
ϕ_2	0.0023	0.0026
Ψ_{22}	0.0106	0.0019
Poultry		
τ_{31}	-0.0294	0.0104
τ_{32}	-0.0128	0.0130
τ_{33}	0.0074	0.0131
β_3	-0.0794	0.0274
ϕ_3	0.0106	0.0015
Ψ_{33}	0.0063	0.0011
Indicator Equations		
Λ_{y21}	0.1126	0.0130
$\Theta_{\epsilon 11}$	0.0268	0.0012
$\Theta_{\epsilon 22}$	0.2229	0.0388
$\Theta_{\epsilon 12}$	-0.0078	0.0011
Cause Equation		
ϕ	0.0036	0.0016
Γ_{11}	2.4600	0.1107
Γ_{12}	3.1030	1.2100
Ψ_{44}	0.2008	0.0355

Table 21. DYMIMIC Price and Expenditure Elasticities

Price Elasticity

	Beef	Pork	Poultry
Beef	-1.1170	-0.0455	-0.1983
Pork	0.1612	-0.9605	0.2753
Poultry	0.0676	0.0720	-0.8913

Price Elasticity (Approximation)

	Beef	Pork	Poultry
Beef	-1.1260	-0.0502	-0.2133
Pork	0.1710	-0.9553	0.2917
Poultry	0.0779	0.0773	-0.8741

Expenditure Elasticity

Beef	1.4380
Pork	0.5220
Poultry	0.4988

Table 22. DYMIMIC Latent Variable and Latent Effect

Year	Latent	t-value	Beef	Pork	Poultry
1950	-2.1650	-135.3971	0.0278	-0.0049	-0.0229
1951	-2.2070	-138.0238	0.0283	-0.0050	-0.0233
1952	-2.2260	-139.2120	0.0286	-0.0050	-0.0235
1953	-2.2590	-141.2758	0.0290	-0.0051	-0.0239
1954	-2.3660	-147.9675	0.0303	-0.0053	-0.0250
1955	-2.3690	-148.1551	0.0304	-0.0053	-0.0251
1956	-2.3930	-149.6560	0.0307	-0.0054	-0.0253
1957	-2.4260	-151.7198	0.0311	-0.0055	-0.0257
1958	-2.4020	-150.2189	0.0308	-0.0054	-0.0254
1959	-2.3690	-148.1551	0.0304	-0.0053	-0.0251
1960	-2.3470	-146.7792	0.0301	-0.0053	-0.0248
1961	-2.2870	-143.0269	0.0293	-0.0052	-0.0242
1962	-2.2410	-140.1501	0.0288	-0.0051	-0.0237
1963	-2.1990	-137.5235	0.0282	-0.0050	-0.0233
1964	-2.0870	-130.5191	0.0268	-0.0047	-0.0221
1965	-2.0000	-125.0782	0.0257	-0.0045	-0.0212
1966	-1.9530	-122.1388	0.0251	-0.0044	-0.0207
1967	-1.7740	-110.9443	0.0228	-0.0040	-0.0188
1968	-1.5030	-93.9962	0.0193	-0.0034	-0.0159
1969	-1.2150	-75.9850	0.0156	-0.0027	-0.0129
1970	-1.0110	-63.2270	0.0130	-0.0023	-0.0107
1971	-0.7603	-47.5485	0.0098	-0.0017	-0.0080
1972	-0.4268	-26.6917	0.0055	-0.0010	-0.0045
1973	-0.0354	-2.2120	0.0005	-0.0001	-0.0004
1974	0.2884	18.0363	-0.0037	0.0007	0.0031
1975	0.7112	44.4778	-0.0091	0.0016	0.0075
1976	1.1180	69.9187	-0.0143	0.0025	0.0118
1977	1.6120	100.8130	-0.0207	0.0036	0.0170
1978	1.9680	123.0769	-0.0253	0.0044	0.0208
1979	2.3650	147.9049	-0.0303	0.0053	0.0250
1980	2.8950	181.0507	-0.0371	0.0065	0.0306
1981	3.3500	209.5059	-0.0430	0.0076	0.0354
1982	3.6490	228.2051	-0.0468	0.0082	0.0386
1983	4.0310	252.0951	-0.0517	0.0091	0.0426
1984	4.5280	283.1770	-0.0581	0.0102	0.0479
1985	5.2260	326.8293	-0.0670	0.0118	0.0553
1986	6.2430	390.4315	-0.0801	0.0141	0.0660
1987	7.0390	440.2126	-0.0903	0.0159	0.0744

Table 23. Latent Preference Elasticities

Year	Beef	Pork	Poultry
1950	0.0528	-0.0155	-0.1445
1951	0.0539	-0.0157	-0.1472
1952	0.0543	-0.0159	-0.1485
1953	0.0551	-0.0161	-0.1507
1954	0.0577	-0.0169	-0.1578
1955	0.0578	-0.0169	-0.1581
1956	0.0584	-0.0171	-0.1597
1957	0.0592	-0.0173	-0.1618
1958	0.0586	-0.0171	-0.1602
1959	0.0578	-0.0169	-0.1581
1960	0.0573	-0.0167	-0.1566
1961	0.0558	-0.0163	-0.1526
1962	0.0547	-0.0160	-0.1495
1963	0.0537	-0.0157	-0.1467
1964	0.0509	-0.0149	-0.1392
1965	0.0488	-0.0143	-0.1334
1966	0.0477	-0.0139	-0.1303
1967	0.0433	-0.0127	-0.1184
1968	0.0367	-0.0107	-0.1003
1969	0.0297	-0.0087	-0.0811
1970	0.0247	-0.0072	-0.0674
1971	0.0186	-0.0054	-0.0507
1972	0.0104	-0.0030	-0.0285
1973	0.0009	-0.0003	-0.0024
1974	-0.0070	0.0021	0.0192
1975	-0.0174	0.0051	0.0475
1976	-0.0273	0.0080	0.0746
1977	-0.0393	0.0115	0.1075
1978	-0.0480	0.0140	0.1313
1979	-0.0577	0.0169	0.1578
1980	-0.0707	0.0207	0.1932
1981	-0.0817	0.0239	0.2235
1982	-0.0890	0.0260	0.2435
1983	-0.0984	0.0288	0.2689
1984	-0.1105	0.0323	0.3021
1985	-0.1275	0.0373	0.3486
1986	-0.1523	0.0445	0.4165
1987	-0.1718	0.0502	0.4696

Table 24. Estimated Taste Effect On Consumer Demand

	Beef	Pork	Poultry
1950-1987	-0.2246	0.0657	0.6141
1970-1987	-0.2014	0.0589	0.5507
1980-1987	-0.1141	0.0334	0.3118
Predicted Effect (by 2000)	-0.3379	0.0988	0.9238

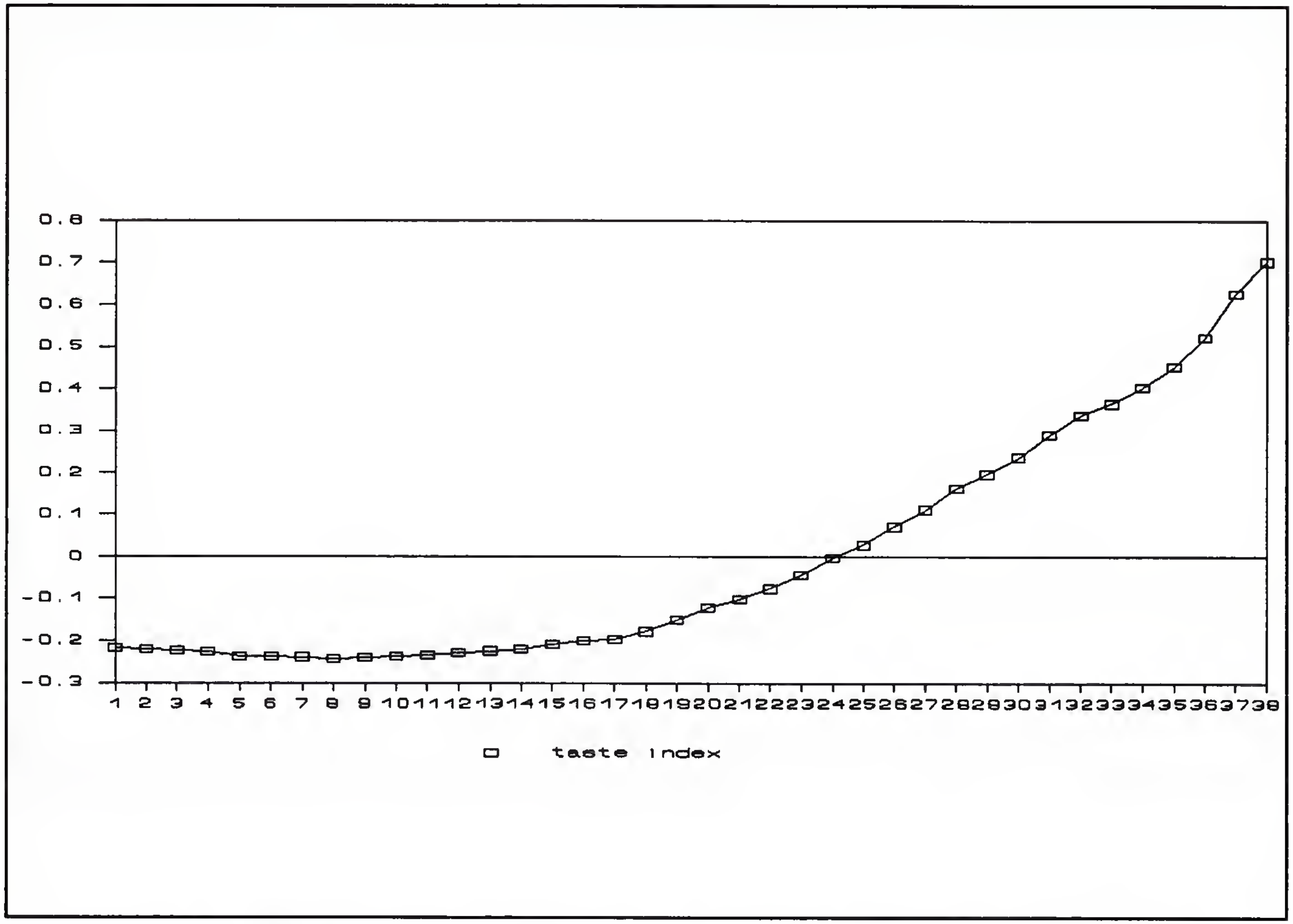

Figure 4. Taste Index (1950-1987) With Its Mean Zero And Scale Equivalent To Milk Ratio.

CHAPTER 6
SUMMARY AND CONCLUSIONS

A latent variable is a variable that is not observable, it is usually called variable with measurement error, and seldom it is given much attention in econometrics. Consumer taste is a latent variable since it can not be directly measured.

There is a wide presumption that consumer taste changes are responsible for declining per capita beef consumption and increasing poultry consumption. Research to date has yielded mixed results. The main critism of many studies is that they failed to separate specification error from model shock which is often attributed to taste change. Furthermore, since taste is not included in the estimated model, it will be very difficult, if not impossible, to separate taste effect from other demand shocks, let alone specification errors. The models which have included a taste proxy in their models (e.g. Brown and Shrader, 1990) used standard regression techniques and gave too much weight to a single data series as proxy variable. In this dissertation, the assumption of constant taste in demand models is relaxed in the underlying utility function. Then

latent taste variable enters into both the indirect utility and cost function as another variable besides prices and income. Factor analysis and causal path analysis are combined into a general structural equation model to estimate the taste variable in a meat demand system. A latent taste variable is defined to be a function of its cause variables and itself is represented by some indicators.

In this research, a multiple indicator structural equation model is first estimated, with the AIDS and Rotterdam model serving as the demand structures. Two indicators used in this model are low fat milk consumption ratio and the cholesterol index respectively. They represent consumer taste change because of health concerns. The second model is a Multiple Indicator and Multiple Cause (MIMIC) model with the low fat milk consumption ratio and egg consumption as indicators, and cholesterol and percentage of married working women as cause variables. The taste variable in this case is affected by both health concerns and consumer demand for convenience. The working women percentage shows the trend of household demand for convenient, easy to cook meat; while egg consumption, in addition to health reasons, also represents consumer demand for convenience at the breakfast table. The third model is a dynamic MIMIC model which allows the taste variable to follow a auto-regressive path. This model is set in a state

space framework and estimated by Kalman filtering and smoothing.

The result of this study shows significant preference change in beef and poultry demands. These results are consistent throughout the three models. The preference change has a negative effect on beef demand and a positive effect on poultry consumption. Its effect on pork demand has been insignificant. It is estimated that taste change in beef demand has decreased beef consumption by about twenty-two percent; and poultry consumption has increased by fifty-five percent within the data range. The inclusion of the convenience consideration in taste change only slightly strengthened the speed of taste adjustment.

Econometric models used to identify structural changes by diagnosing changes of coefficients in demand functions overlook the fact that preference change is a smooth time diffusing process, not an abrupt change. The preference change is found to be a smooth process. There is no evidence to support the notion that structural (preference) change occurred abruptly in that period, all we can conclude is that structural change has indeed occurred for beef and poultry demand over the past three decades, and that the trend continues.

Good indicator and cause variables are important to structural equation models. Other variables should be used if available to compare the results. But compared with the

practice of regression on a taste proxy, the structural equation model has greatly decreased model dependence on data. This is evident when the estimated latent taste variable is compared with the indicator and cause variable. Even in the simplest model, with only indicator variables, the estimated latent taste variable is a smooth monotonic changing series. It is quite unlike that the rough low fat milk ratio indicator series which serves as base indicators for taste variables. This shows that the structural latent variable model decreased model dependence on proxy taste variables as compared with regression models using an exogenous proxy variable. Latent variable is an optimal combination of the indicator and cause variables. None-zero variances of the disturbance terms for the indicator and cause variable equations reconfirm that the indicator and cause variables are measured with error and should not be used individually or together without accounting for this source of measurement error.

From 1970-1987, taste change alone has caused the beef demand to decline by 17 percent, increase pork and poultry demand by 5 and 47 percent respectively. Per capita consumption of beef decreased 13 percent, pork and poultry increased 5 and 60 percentage respectively in the same period. The difference can be attributed to price and income changes. Beef demand is expenditure elastic, the increase of beef expenditure offset some of the taste

induced demand decline. Actual poultry consumption increased more than taste induced increase because the relative price of poultry decreased in the same period.

Structural change can be induced by either demand or supply changes. This study analyses demand change by assuming uniform and constant supply shock. It would be no surprising that studies assuming constant demand shock may find supply change in some meat productions. It would be enlightening to address the demand and supply changes simultaneously and identify whether and how much demand change has changed consumer consumption. This is an interesting topic for further studies.

Some researchers used disaggregate data (steak, roast, ground beef, whole bird, etc.) to study the issue of structural change. They found no evidence to support the notion of taste change and concluded that structural changes are mainly from aggregation bias (Eales and Unnevehr, 1988). It would be interesting to run a latent variable taste model using disaggregate data to compare the results. It can give us a further idea about the relationship between data aggregation and structural changes.

One thing can be improved in this study is that in the DYMIMIC model, the residual autocorrelation should be included into specification and test its presence as done by Engle and Watson (1981). The taste variable may also follow a higher degree of auto-regression (two lagged taste

variables, for instance). A model of this nature is very time consuming in terms of computation, but would greatly strengthen the performance of the dynamic model.

APPENDIX A
SUMMERY OF SOME STUDIES ON STRUCTURAL CHANGE IN RETAIL MEAT DEMAND

Author(s)	Date	Meats	Methods	Findings
Chavas (1982)	Annual 1950-70	poultry beef pork	quantity dependent with random coefficients in demand system	structural change in beef and poultry in post-1975 period
Nyankori & Miller (1982)	quarterly 1960-79	beef, pork chicken turkey	quantity dependent, single equation spline model	structure change for beef and chicken not for pork
Wohlgenant (1982,1986)	annual	beef pork poultry	Rotterdam system standardized for nutrition component over time	structural change for beef and poultry
Moschini & Meilke (1984)	querterly 1966-1981	beef	quantity depended single equation Box-Cox transformation	no structural chenge although elasticity changes
Breschler (1983)	annual 1950-82	beef,pork	price dependent single equation	structural change in beef and pork; new switching regression beef st post 1971;pork post-1969
Dahlgran (1987)	annual 1950-85	poultry beef pork	Rotterdam model gradual switching regression	demand elasticities shifted in 1970s but no permanent change
Eales &Unnevehr (1988)	annual 1965-85	beef chicken	DAIDS disaggregated meats	structural change but not from health concern; grading and convenience
Moschini &Meilke (1989)	quarterly 1967-88	beef pork chicken fish	AIDS switching regression	structural change against beef, for chicken and fish, neutral to pork
Chalfant &Alston (1989)	annual 1947-78	beef pork chicken	non-parametric model	no evidence of structural change found

APPENDIX B
GAUSS PROGRAM FOR MIMIC MODEL

```
use optmum;

@ -----------    MIMIC.GAU        --@

" three goods AIDS model with two indicators and covariance
elements";

load p1[38,6] = a:price.prn;
load q1[38,12] = a:quant.prn;
load ww[38,3] =a:women.prn;
ww[.,3]=ww[.,3];


let chole[22,1]=13 134 297 418 534 635 744 888 1044 1221 1370 1507
            1612 1742 1846 1978 2128 2305 2519 2779 3078 3368;
chole=.001*chole; chole=zeros(16,1)|chole;


p=p1[.,2:4]; p=10*p; q=q1[.,2:4];
lx=ln(sumc((p.*q)'));
w=(p.*q)./sumc((p.*q)');
lp=ln(p);lq=ln(q);

lpp=sumc((w.*lp)');             /*stone index*/

        load tst=a:\mmc\l;tst=tst';
tx2=lp[.,1:3]~(lx-lpp);
tx=tx2-(meanc(tx2))'; tx=tx~tst;
            /*Intercepts are eliminated from AIDS
                by taking exogenous*/

tx1=tx[.,1:4];                  /*exogenous variables*/

w1=w[.,1:3];
w=w1-(meanc(w1))';

b1=inv(tx'*tx)*(tx'*w);
        /*the AIDS h/n restricted coefficients*/
```

```
stt=(w-tx*b1)'*(w-tx*b1)/38;
                                /*cov. of residual of AIDS*/

indii=(q1[.,7]./q1[.,6])~(1./Q1[.,5])~CHOLE~WW[.,3];
indi=indii-(meanc(indii))';

lambda1=inv(indi[.,1]'indi[.,1])*(indi[.,1]'indi[.,2]);


theta=indi[.,1:2]-((indi[.,1])*(1~(lambda1)));
theta=(theta'theta)./38;

vdelta=(indi[.,3:4]'indi[.,3:4])./38;
GAMA1=INV(INDI[.,3:4]'INDI[.,3:4])*(INDI[.,3:4]'INDI[.,1]);
PSI1=INDI[.,1]-INDI[.,3:4]*GAMA1;
PSI1=PSI1'PSI1/38;

xi=indi[.,3:4]~tx1;
y=indi[.,1:2]~w[.,1:2];

z=y~xi; z=z'z./38;          /*cov of x and y*/


b1=vec(b1[.,1:2])'; b12=sqrt((diag(stt))); b2=b12[1:2]';
 b3=(diag(theta))'; b3=sqrt(b3); vdelta1=sqrt(diag(vdelta));
vdelta=(vdelta1')~vdelta[1,2];
cov=stt[1,2]~theta[1,2];
b=b1~b2~b3~(lambda1')~(GAMA1')~PSI1~vdelta~cov;
b[13]=0.3; b[11:14]=abs(b[11:14]);

x1=(indi[.,3:4]~tx1)'(indi[.,3:4]~tx1)./38;
b=b';                   @ b is a column vector @


b[11:14]=abs(b[11:14]); b[18]=abs(b[18]);
b=b[1:18];


proc qfct(b);
local lambday,gama1,thet,beta,phi,gama,n,g,s1,s2,s3,s,psi,m;
 /* the following defines the parameters computed*/

gama1=(b[1:4]')|(b[6:9]');
gama=((b[16:17]')~zeros(1,4))|(zeros(2,2)~gama1);
beta=zeros(3,3); beta[2,1]=b[5];beta[3,1]=b[10];
lambday=zeros(4,3);lambday[1,1]=1;lambday[2,1]=b[15].^2;lambday[3,2]=1;
                    lambday[4,3]=1;
thet=zeros(4,4); thet[1,1]=b[13].^2;thet[2,2]=b[14].^2;
psi=zeros(3,3); psi[1,1]=b[18].^2;psi[2,2]=b[11].^2;psi[3,3]=b[12].^2;
phi=x1;
```

```
s1=lambday*inv(eye(3)-beta)*(gama*phi*gama'+psi)*inv(eye(3)-beta)'*lambday'
   +thet;
S2=lambday*inv(eye(3)-beta)*Gama*phi;
s3=phi;
s=(s1~(s2))|((s2')~s3);

m=19*ln(abs(det(s)))+19*sumc(diag(z*inv(s)));

retp(m); endp;


{x,f,g,h} = optmum(b,&qfct);


"function:";f;
"parameters:";xb=x';xb;
"gradien*t:";g=g';g;
"std errors:"; st=sqrt(diag(h))'; st;
save path = a:\mmc;save f,xb,g,st;



@-------third equation-------------------------------@

b2=-xb[1:5]-xb[6:10];
b=xb[1:5]~b2~xb[11:18];
b[12]=b12[3];
b=b';

y=indi[.,1:2]~w[.,1 3];
z=y~xi;z=z'z./38;


proc qfct(b);
local lambday,gama1,thet,beta,phi,gama,n,g,s1,s2,s3,s,psi,m;
 /* the following defines the parameters computed*/

gama1=(b[1:4]')|(b[6:9]');
gama=((b[16:17]')~zeros(1,4))|(zeros(2,2)~gama1);
beta=zeros(3,3); beta[2,1]=b[5];beta[3,1]=b[10];
lambday=zeros(4,3);lambday[1,1]=1;lambday[2,1]=b[15].^2;lambday[3,2]=1;
                    lambday[4,3]=1;
thet=zeros(4,4); thet[1,1]=b[13].^2;thet[2,2]=b[14].^2;
psi=zeros(3,3); psi[1,1]=b[18].^2;psi[2,2]=b[11].^2;psi[3,3]=b[12].^2;
phi=x1;


s1=lambday*inv(eye(3)-beta)*(gama*phi*gama'+psi)*inv(eye(3)-beta)'*lambday'
   +thet;
S2=lambday*inv(eye(3)-beta)*Gama*phi;
s3=phi;
s=(s1~(s2))|((s2')~s3);
```

```
m=19*ln(abs(det(s)))+19*sumc(diag(z*inv(s)));

retp(m); endp;

{x,f,g,h} = optmum(b,&qfct);


"function:";f1=f;f1;
"parameters:";xb1=x';xb1;
"gradien*t:";g=g';g;
"std errors:"; st1=sqrt(diag(h))'; st1;
save path = a:\mmc;save f1,xb1,st1;



@------latent taste (difference) variable---------------@
b=xb[.,1:4]|xb[.,6:9]|xb1[.,6:9];

y=(w-tx1*b')';y=y|(indi[.,2]');
ec=(st[11:12]~st1[12]~abs(xb[14])).^2; v=diagrv(eye(4),ec);
d=xb[5]~xb[10]~xb1[10]~xb[15];d=d';

l=inv(d'*inv(v)*d)*(d'*inv(v)*y);
"the latent variable (delta-k):"; l; save l;
al=sumc(l')/rows(l');"the average of latent variable:";al;
vl=sqrt(inv(d'*inv(v)*d));
"the std of latent variable:";vl;  save al,vl;

@-------------elasticity --------------------------@
ep1=-eye(3)+xb[.,1:3]./w1[16,.]'-(xb[.,4].*(w1[16,.]'./w1[16,.]))';
ep2=-eye(3)+xb[.,1:3]./w1[36,.]'-(xb[.,4].*(w1[36,.]'./w1[36,.]))';
ei1=xb[.,4]./w1[16,.]'+ones(3,1);
ei2=xb[.,4]./w1[36,.]'+ones(3,1);


XBB=(xb[1:5]|xb[6:10]|xb1[6:10]); W1=MEANC(W1);
A=-EYE(3)+(XBB[.,1:3])./(W1) -(XBB[.,4]).*(W1./(W1'))';
B=XBB[.,4];B=B./(W1);
C=(W1.*MEANC(LP))';
E=INV(B*C+EYE(3))*(A+EYE(3))-EYE(3);
"PRICE ELASTICITY MATRIX";E;
E1=XBB[.,4]./W1+ONES(3,1);
"INCOME ELASTICITY VECTOR:";E1;
E2=((L')*(XBB[.,5])')./(W1');
"LATENT VARIABLE (DIFFERENCE WITH MEAN) ELASTICITY MATRIX";E2;
"the price elasticity assuming expenditure shares are
constant:";A;e;

save e,e1,e2,a,ep1,ep2,ei1,ei2;
```

APPENDIX C
GAUSS PROGRAM FOR DYMIMIC MODEL

```
use opt386;

@ KALMAN.SDT -----------    DYMIMIC    ------------@


" three goods AIDS model with two indicators and covariance
elements";
load path =a;
load p1[38,6] =a:price.prn;
load q1[38,12] =a:quant.prn;
load ww[38,3] =a:women.prn;
ww[.,3]=ww[.,3];
let chole[22,1]=13 134 297 418 534 635 744 888 1044 1221 1370 1507
                1612 1742 1846 1978 2128 2305 2519 2779 3078 3368;
chole=.001*chole; chole=zeros(16,1)|chole;

p=p1[.,2:4]; p=10*p; q=q1[.,2:4];
lx=ln(sumc((p.*q)'));
w=(p.*q)./sumc((p.*q)');
lp=ln(p);lq=ln(q);

lpp=sumc((w.*lp)');             /*stone index*/

load tst=a:\kalman\smt1\a00;

tx2=lp[.,1:3]~(lx-lpp);
tx=tx2-(meanc(tx2))'; tx=tx~tst;


w1=w[.,1:3];
w=w1-(meanc(w1))';

bb1=inv(tx'*tx)*(tx'*w);
                /*the AIDS h/n restricted coefficients*/

st=(w-tx*bb1)'*(w-tx*bb1)/38;
                /*cov. of residual of AIDS*/
```

```
indii=(q1[.,7]./q1[.,6])~(1./Q1[.,5])~CHOLE~WW[.,3];
indi=indii-(meanc(indii))';

lambda1=inv(indi[.,1]'indi[.,1])*(indi[.,1]'indi[.,2]);


theta=indi[.,1:2]-((indi[.,1])*(1~(lambda1)));
theta=(theta'theta)./38;

vdelta=(indi[.,3:4]'indi[.,3:4])./38;
GAMA1=INV(INDI[.,3:4]'INDI[.,3:4])*(INDI[.,3:4]'INDI[.,1]);
PSI1=INDI[.,1]-INDI[.,3:4]*GAMA1;
PSI1=PSI1'PSI1/38;

b1=vec(bb1[.,1:2])'; b12=sqrt((diag(st))); b2=b12[1:2]';
    b3=(diag(theta))'; b3=sqrt(b3); vdelta1=sqrt(diag(vdelta));
vdelta=(vdelta1')~vdelta[1,2];
cov=st[1,2]~st[2,1]~theta[1,2]~theta[2,1];
b=b1~b2~b3~(lambda1')~(GAMA1')~PSI1~vdelta~cov;


b0=0~(gama1')~psi1~b1[5]~b1[10]~(lambda1)~b1[1:4]~b1[6:9]~b2~b3;
b0[18]=.3;
b=b0';


y=w[.,1:2]~indi[.,1:2];
z=tx[.,1:4];
m=indi[.,3:4];
xdat=y~z~w;



proc kalman(b);

    local phi,gama,v,sigoo,signo,signn,a,xoo,xno,xnn,icount,s,xo,
        h,gao,alfa,beta,eta,nobs,loglikli,ht,k1,lht;
    gama=zeros(1,2);
    beta=zeros(4,4);
    alfa=zeros(4,1);
    h=zeros(4,4);

    let sigoo=50000;  load s=a:\kalman\smt1\p00;sigoo=s[1];
    let xoo=0;        load xo=a:\kalman\smt1\a00;xoo=xo[1];

    phi=b[1];
    gama[1,1]=b[2];   gama[1,2]=b[3];
    v=b[4].^2;
    alfa[1,1]=b[5]; alfa[2,1]=b[6];alfa[3,1]=1;alfa[4,1]=b[7];
    beta[1,1:4]=b[8:11]';
    beta[2,1:4]=b[12:15]';
    h[1,1]=b[16].^2;h[2,2]=b[17].^2;h[3,3]=b[18].^2;h[4,4]=b[19].^2;
```

```
    nobs=rows(y)-1;
    icount=0;
    eta=zeros(rows(y),cols(y));
    lht=zeros(rows(y),1);
    gao=zeros(rows(y),1);

    do until icount>nobs;
        icount=icount+1;
        signo=phi*sigoo*phi'+v;
        signn=signo-signo*alfa'*inv(alfa*signo*alfa'+h)*alfa*signo;
        xno=phi*xoo + gama*m[icount,.]';
        k1=signo*alfa'*inv(alfa*signo*alfa'+h);
        eta[icount,.]=(y[icount,.]'-alfa*xno-beta*z[icount,.]')';
        xnn=xno+k1*eta[icount,.]';
        ht=alfa*signo*alfa'+h;
        lht[icount]=log(abs(det(ht)));
        gao[icount]=eta[icount,.]*inv(ht)*eta[icount,.]';
        sigoo=signn;
        xoo=xnn;

    endo;

    retp( .5*sumc(lht)+ .5*sumc(gao));
    endp;

 {bhat,f,g,cov}=optmum(b,&kalman);
" function";f=f;f;
"parameters"; bhat1=bhat';bhat1;
"std errors";sdt1=sqrt(diag(cov))';sdt1;
      save path =a:\kalman;save f,bhat1,sdt1;



/*------------third equation------------------------------*/


b1=vec(bb1[.,1 3])'; b12=sqrt((diag(st))); b2=b12[1 3]';

b0=.4~(gama1')~psi1~b1[5]~b1[10]~(lambda1)~b1[1:4]~b1[6:9]~(b2)~b3;

b=b0';


y=w[.,1 3]~indi[.,1:2];
z=tx[.,1:4];
m=indi[.,3:4];
xdat=y~z~w;
```

```
proc kalman(b);

    local phi,gama,v,sigoo,signo,signn,a,xoo,xno,xnn,icount,s,xo,
         h,gao,alfa,beta,eta,nobs,loglikli,ht,k1,lht;
    gama=zeros(1,2);
    beta=zeros(4,4);
    alfa=zeros(4,1);
    h=zeros(4,4);

    let sigoo=50000;      load s=a:\kalman\smt2\p00;sigoo=s[1];
    let xoo=0;            load xo=a:\kalman\smt2\a00;xoo=xo[1];

    phi=b[1];
    gama[1,1]=b[2];   gama[1,2]=b[3];
    v=b[4].^2;
    alfa[1,1]=b[5]; alfa[2,1]=b[6];alfa[3,1]=1;alfa[4,1]=b[7];
    beta[1,1:4]=b[8:11]';
    beta[2,1:4]=b[12:15]';
    h[1,1]=b[16].^2;h[2,2]=b[17].^2;h[3,3]=b[18].^2;h[4,4]=b[19].^2;



    nobs=rows(y)-1;
    icount=0;
    eta=zeros(rows(y),cols(y));
    lht=zeros(rows(y),1);
    gao=zeros(rows(y),1);

    do until icount>nobs;
        icount=icount+1;
        signo=phi*sigoo*phi'+v;
        signn=signo-signo*alfa'*inv(alfa*signo*alfa'+h)*alfa*signo;
        xno=phi*xoo + gama*m[icount,.]';
        k1=signo*alfa'*inv(alfa*signo*alfa'+h);
        eta[icount,.]=(y[icount,.]'-alfa*xno-beta*z[icount,.]')';
        xnn=xno+k1*eta[icount,.]';
        ht=alfa*signo*alfa'+h;
        lht[icount]=log(abs(det(ht)));
        gao[icount]=eta[icount,.]*inv(ht)*eta[icount,.]';
        sigoo=signn;
        xoo=xnn;

    endo;

    retp( .5*sumc(lht)+ .5*sumc(gao));
    endp;

 {bhat,f,g,cov}=optmum(b,&kalman);
" function";f1=f;f1;
"parameters"; bhat2=bhat';bhat2;
"std errors";sdt2=sqrt(diag(cov))';sdt2;
      save path =a:\kalman;save f1,bhat2,sdt2;
```

```
@ SMOOTHER.KALMAN.SDT -----------    DYMIMIC    ------------@

/* --------------------smoother (I) ---------------------*/


                    load b=a:\kalman\bhat1; b=b';

y=w[.,1:2]~indi[.,1:2];
z=tx[.,1:4];
m=indi[.,3:4];
xdat=y~z~w;


    gama=zeros(1,2);
    beta=zeros(4,4);
    alfa=zeros(4,1);
    h=zeros(4,4);


    let sigoo=50000;   load s=a:\kalman\smt1\p00;sigoo=s[1];
    let xoo=0;         load xo=a:\kalman\smt1\a00;xoo=xo[1];

    phi=b[1];
    gama[1,1]=b[2];   gama[1,2]=b[3];
    v=b[4].^2;
    alfa[1,1]=b[5]; alfa[2,1]=b[6];alfa[3,1]=1;alfa[4,1]=b[7];
    beta[1,1:4]=b[8:11]';
    beta[2,1:4]=b[12:15]';
    h[1,1]=b[16].^2;h[2,2]=b[17].^2;h[3,3]=b[18].^2;h[4,4]=b[19].^2;



    nobs=rows(y)-1;
    icount=0;
    eta=zeros(rows(y),cols(y));
    lht=zeros(rows(y),1);
    gao=zeros(rows(y),1);
    a=zeros(rows(y),1);
    p=zeros(rows(y),1);
    ppre=zeros(rows(y),1);


    do until icount>nobs;
        icount=icount+1;
        signo=phi*sigoo*phi'+v;
        signn=signo-signo*alfa'*inv(alfa*signo*alfa'+h)*alfa*signo;
        xno=phi*xoo  +  gama*m[icount,.]';
        k1=signo*alfa'*inv(alfa*signo*alfa'+h);
        eta[icount,.]=(y[icount,.]'-alfa*xno-beta*z[icount,.]')';
```

```
        xnn=xno+k1*eta[icount,.]';
        ht=alfa*signo*alfa'+h;
        lht[icount]=log(abs(det(ht)));
        gao[icount]=eta[icount,.]*inv(ht)*eta[icount,.]';
        sigoo=signn;
        xoo=xnn;
        p[icount]=signn;
        a[icount]=xnn;
        ppre[icount]=signo;
    endo;

      p00=zeros(rows(y),1);
      a00=zeros(rows(y),1);

      p00[38]=p[38]; a00[38]=a[38];

      i=38;
      do until i<2;
         i=i-1;
         pstar=p[i]*phi*(1/ppre[i+1]);
         a00[i]=a[i]+pstar*(a00[i+1]-phi*a[i]);
         p00[i]=p[i]+pstar*(p00[i+1]-ppre[i])*pstar;

      endo;
         save path=a:\kalman\smt1;save a00,p00;
                format 7,3;    a00';p00';



/*--------------------smoother (II) ---------------------*/

                    load b=a:\kalman\bhat2;  b=b';


y=w[.,1 3]~indi[.,1:2];
z=tx[.,1:4];
m=indi[.,3:4];
xdat=y~z~w;



    gama=zeros(1,2);
    beta=zeros(4,4);
    alfa=zeros(4,1);
    h=zeros(4,4);


    let sigoo=50000; load s=a:\kalman\smt2\p00;sigoo=s[1];
    let xoo=0;       load xo=a:\kalman\smt2\a00;xoo=xo[1];

    phi=b[1];
    gama[1,1]=b[2];   gama[1,2]=b[3];
```

```
v=b[4].^2;
alfa[1,1]=b[5]; alfa[2,1]=b[6];alfa[3,1]=1;alfa[4,1]=b[7];
beta[1,1:4]=b[8:11]';
beta[2,1:4]=b[12:15]';
h[1,1]=b[16].^2;h[2,2]=b[17].^2;h[3,3]=b[18].^2;h[4,4]=b[19].^2;


nobs=rows(y)-1;
icount=0;
eta=zeros(rows(y),cols(y));
lht=zeros(rows(y),1);
gao=zeros(rows(y),1);
a=zeros(rows(y),1);
p=zeros(rows(y),1);
ppre=zeros(rows(y),1);


do until icount>nobs;
    icount=icount+1;
    signo=phi*sigoo*phi'+v;
    signn=signo-signo*alfa'*inv(alfa*signo*alfa'+h)*alfa*signo;
    xno=phi*xoo + gama*m[icount,.]';
    k1=signo*alfa'*inv(alfa*signo*alfa'+h);
    eta[icount,.]=(y[icount,.]'-alfa*xno-beta*z[icount,.]')';
    xnn=xno+k1*eta[icount,.]';
    ht=alfa*signo*alfa'+h;
    lht[icount]=log(abs(det(ht)));
    gao[icount]=eta[icount,.]*inv(ht)*eta[icount,.]';
    sigoo=signn;
    xoo=xnn;
    p[icount]=signn;
    a[icount]=xnn;
    ppre[icount]=signo;
endo;

    p00=zeros(rows(y),1);
    a00=zeros(rows(y),1);

    p00[38]=p[38]; a00[38]=a[38];
    i=38;
    do until i<2;
        i=i-1;
        pstar=p[i]*phi*(1/ppre[i+1]);
        a00[i]=a[i]+pstar*(a00[i+1]-phi*a[i]);
        p00[i]=p[i]+pstar*(p00[i+1]-ppre[i])*pstar;

    endo;
        save path=a:\kalman\smt2;save a00,p00;
                    a00';p00';
```

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BIOGRAPHICAL SKETCH

Xiaoming Gao, son of Gao Jisheng and Nian Guizhen, was born on October 9, 1962, in Lanzhou, China. He spent his sweet and memorable childhood in a large family in Xiangyong, an industrial city in northwest China. In 1969, his family was sent to a countryside village to undergo "re-education through labor" in the Cultural Revolution, where he spent eight school years of turmoil and hardship in a People's Commune. In 1978, when universities were re-opened after a decade of closing, inspired by his childhood experience, he went to the Northwest Agriculture University to study political and agricultural economics, where he received his B.S. degree in agricultural economics in 1982.

He worked in the Institute of Agricultural Economics, Chinese Academy of Agricultural Sciences as a junior research assistant for three years after 1982. He was granted a scholarship from the Ford Foundation in 1985 and started his M.S. program at the University of Florida. He got his M.S. degree in December 1988. He has been a member of the Honor Society of Agriculture (Gamma Sigma Delta) since 1986.

He is married to Xiaoli Zhang, and they have a daughter Alice Xi Gao.

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

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